Planting the Seeds for Success: Why Women in STEM Do Not Stick in the Field

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Abstract

Women are underrepresented in both STEM college majors and STEM jobs. Even with a STEM college degree, women are significantly less likely to work in a STEM occupation than their male counterparts. This paper investigates whether men and women possess different ability distributions and examines how much the gender gap in major choice and job choice can be explained by gender differences in ability sorting. I use Purdue University's administrative data that contain every Purdue student's academic records linked to information on their first job. I apply an extended Roy model of unobserved heterogeneity allowing for endogenous choice with two sequential optimizing decisions: the choice between a STEM and non-STEM major and the choice between a STEM and non-STEM job. I find that abilities are significantly weaker determinants of major choice for women than for men. High-ability women give up $13,000–$20,000 in annual salary by choosing non-STEM majors. Those non-STEM high-ability women make up only 5.6% of the female sample, but their total gains—had they made the same decision as men—explain about 9.4% of the gender wage gap. Furthermore, the fact that female STEM graduates are less likely to stay in STEM is unrelated to the differences in ability sorting. Instead, women's home region may be important in women's job decisions; female STEM graduates who return to their home state are more likely to opt out of STEM.

Keywords: Gender Differences in STEM, Choice of College Major, Choice of Job, Ability Sorting

JEL Classification: I20, I23, J16, J24, J31

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†Click here or go to https://sites.google.com/site/gabixuanjiang/research for the latest version.

‡1945 N. High St., 383 Arps Hall, Columbus, OH 43210; email: gabijiang@purdue.edu The author does not have access to any information leading to the identification of individuals in the data. All data analysis was carried out in a secure server.

1 Introduction

Women are underrepresented in science, technology, engineering and mathematics (STEM) college majors and occupations. While nearly as many women hold college degrees as men overall, they make up only about a third of all STEM degree holders. Although women fill close to half of all jobs in the U.S. economy, they hold less than a quarter of STEM jobs. Moreover, women with STEM college degrees are less likely than their male counterparts to work in STEM occupations. About 40 percent of men with STEM college degrees work in STEM jobs, while only 23 percent of women with STEM degrees work in STEM jobs (Noonan, 2017).

Why is the lack of women in the STEM field a concern? First, we face a scarcity of STEM workers in many industries, even though STEM jobs are among the best-paying jobs (Xue and Larson, 2015). Attracting and retaining more women in STEM will help with unfilled positions. Second, when women are not seen as equal to men in STEM, young women lack role models to motivate them and help them envision themselves in those positions. They are deterred by the idea that STEM is a "man's field" where girls do not belong (Shapiro and Williams, 2012). Last, when women are not involved in STEM, products, services and solutions are designed by men and according to their user experiences. The needs and desires that are unique to women may be overlooked (Fisher and Margolis, 2002; Clayton et al., 2014).

The first research question of this paper is how much of the gender gap in choice of college major and choice of job can be explained by gender differences in sorting on abilities. There is abundant literature that covers the issue of ability sorting in choice of college major (Arcidiacono, 2004; Arcidiacono et al., 2012; Wiswall and Zafar, 2015a; Humphries et al., 2017) and that of gender differences in choice of college major(Polachek, 1978, 1981; Daymont and Andrisani, 1984; Blakemore and Low, 1984; Turner and Bowen, 1999; Dickson, 2010; Ahn et al., 2015; Eccles, 2007; Trusty, 2002; Ethington and Woffle, 1988; Hanson et al., 1996). Yet the two elements—*ability sorting in choice of college major* and *gender differences*—have rarely been linked. My second question is, by not choosing a STEM major or a STEM job, do women leave any money on the table; if so, how much? Third, why are female STEM degree holders more likely to leave STEM than their male counterparts?

I apply an extended Roy model of unobserved heterogeneity to explore the endogenous choices of major and job and, more importantly, the gender differences in these choices. The model involves two sequential optimizing decisions separately estimated for men and women: one chooses between graduating with a STEM degree and a non-STEM degree; after getting a STEM degree, one chooses between a STEM occupation and a non-STEM occupation. My model relies on the identification of two latent abilities, general intelligence and extra mathmatical ability, to deal with sequential selections of major and job. Most of the literature (Arcidiacono, 2004; Long et al., 2015; Altonji et al., 2016) use standardized test scores, such as SAT scores, as measures of ability. Those test scores, however, should be considered only as proxies or functions of true abilities (Carneiro et al., 2003; Heckman et al., 2006; Sarzosa and Urzúa, 2015; Prada et al., 2017). Moreover, the identification strategy here assumes a mixture of normals for the distributions of both latent abilities, which avoids the restriction for them being normal and guarantees the flexibility of the functional forms the latent abilities could take.

The data—Purdue University's administrative (Registrar) data—that I am use fulfill the requirement of the identification of the two latent abilities. They contain the academic records of Purdue undergraduate students who graduated between 2005–2014 and are linked to their first destination survey, conducted by the Purdue

Center for Career Opportunities. The data provide rich information on individuals' high school GPA, standardized test scores (ACT English, ACT Reading, ACT Math and ACT Science), and entire college transcripts data.

I find that the distributions of abilities at the start of college are different between genders; however, gender differences in abilities cannot explain the huge gender gap in choices of majors and jobs. Abilities are significantly weaker determinants of choice of major for women than for men. In fact, high-ability men are more likely to choose STEM majors than high-ability women. Specifically, a one-standard-deviation increase in an average woman's general intelligence will increase her likelihood of graduating with a STEM degree by 17.2 percentage points while that number is 23.4 for an average man. A one-standard-deviation increase in the extra mathematical ability of an average woman will increase her probability of graduating with a STEM degree by 9.5 percentage points; the same change will increase an average man's likelihood of graduating with a STEM degree by 14 percentage points. The finding is consistent with the recent findings in Ahn et al. (2015), which suggests that women are less sensitive to or more critical about their abilities. Alternatively, other characteristics unobserved by the researcher could be more dominant in women's decisions about college major. For my second research question, I find that high-ability women leave large amounts of money on the table by choosing non-STEM majors. A counterfactual analysis shows that a high-ability woman gives up \$13,000–\$20,000 in annual salary by choosing a non-STEM majors. These non-STEM, high-ability women make up only 5.6% of the female sample, but their earning losses explain about 9.4% of the gender wage gap[1].

The existing literature on this topic has focused on students' choices of college majors and the policy implications of attracting students to STEM majors. How-

[1]The gender wage gap—\$8,198—is calculated by subtracting the averaged Purdue's female graduates annual salary by the averaged Purdue's male graduates annual salary.

ever, the career outcomes of STEM graduates remains unexplored. My model is able to assess the determinants of choice of job by allowing the STEM graduates to choose between STEM and non-STEM jobs conditional on their choice of major. Among both male and female STEM graduates, I find little evidence of sorting on abilities when making a job decision. Thus, the fact that female STEM graduates are less likely to stay in STEM compared to their male counterparts is *not* due to differences in ability sorting. This finding implies that other factors are more important to STEM graduates when making a job decision. Based on full decomposition of the job decision equation, I find that the (Census) region where a student came from[2] may be a major factor in a female STEM graduate's decision to pursue a STEM or non-STEM job. Those who go back to their home state after graduation are more likely to opt out of STEM fields. Although this finding is not conclusive, it paves the way for future research on female STEM graduates' trade-offs between opting out of STEM and returning to their home state.

This study makes three main contributions to the existing literature. First, to the best of my knowledge, this is the first attempt to estimate the gender differences of ability sorting in choice of job. Second, I am the first to document that there is a disproportionate and considerable number of high-ability women choose non-STEM majors, and I quantify the total gains if they had made the same choices as high-ability men. I then use these total gains to explain the gender wage gap. Third, I provide empirical evidence to answer the question of why female STEM graduates are more likely to opt-out of working in STEM fields.

This paper is organized as follows. Section 2 reviews related literature on this subject. Section 3 describes the data I used for the analysis. I then present the model and the measurement system for the unobserved abilities in Section 4. In

[2]This is based on the place where the student attended high school.

Section 5 and Section 6, I show my results and counterfactual analysis, respectively. Section 7 discusses the policy implications. Finally, Section 8 concludes.

2 Related Literature

This paper addresses three branches of literature: choice of college major, gender differences in choice of college major, and gender differences in choice of job.

2.1 Choice of College Major

There is an extensive economic literature on choice of college major. The college major premium and income differences among fields of study have been well documented. Differences in return to majors are as large as differences in return to different levels of education, and even larger than differences in return to college quality (Arcidiacono, 2004; Altonji et al., 2015; Daymont and Andrisani, 1984; James et al., 1989). Most studies find that college students' major decisions are related to expected earnings or their beliefs about future earnings (Altonji et al., 2016; Beffy et al., 2012; Long et al., 2015; Wiswall and Zafar, 2015b). Some studies focus on explaining major choices by abilities sorting. Arcidiacono (2004) finds that selection of major depends on the monetary returns to various abilities, preferences in the workplace, and preferences for studying particular majors in college. He argues that major and workplace preferences are more dominant in major selection, which is consistent with my findings in this paper. Arcidiacono et al. (2012) and Wiswall and Zafar (2015a) show that sorting occurs both on expected earnings and on students' perceptions of their relative abilities to perform in particular majors. Based on a similar framework as my paper, Humphries et al. (2017) decompose the college major premium into labor market returns from multi-dimensional abilities and finds that sorting on abilities primarily explains a college major's enrollment rate and about 50% of students graduating from a college major. However, they do not address gender differences in choice of major and focus only on a male sample.

Major switching behavior has been well documented, too. Some studies suggest that students who perform worse than they expected are more likely to dropout or switch to a less difficult major (Stinebrickner and Stinebrickner, 2013; Arcidiacono, 2004). It is more likely for those with lower ability within a major to switch majors because they are closer to the margin of choosing one major over another (Arcidiacono et al., 2012).

2.2 Gender Differences in Choices of Major

Gender differences within college majors and in the workplace have attracted extensive attention. On one hand, women's choices of college majors appear to contribute to the persistent gender wage gap. On the other hand, it has been a concern of policymakers that women are underrepresented in STEM majors due to the reasons I mention in the introduction.

The gender gap in labor market positions, including the gender wage gap and the gender gap in certain types of jobs, is less attributed to discriminatory hiring practices, but rather more to gender-specific preferences in college majors (Polachek, 1978; Daymont and Andrisani, 1984). This viewpoint has been widely accepted by economists, yet some studies find that educational environments associated with discrimination or stereotyping have played an important role in gender segregation: women who attend coeducational colleges are more likely to choose female-dominated fields than those who attended women's colleges (Solnick, 1995).

More effort has been made to explore gender-specific preferences in the workplace and gender differences in abilities or STEM readiness. For the former, studies have found that gender differences in fertility expectations affect gender differences in the choice of college majors. Young female students with higher expected fertility tend to choose majors that are progressively less subject to atrophy and obsolescence (i.e., history and English), considering the expected time-out-of-the-labor force (Polachek, 1981; Blakemore and Low, 1984). Men care more about pecuniary outcomes and leadership in the workplace, while women are more likely to value opportunities to help others, to contribute to society, and to interact with people (Zafar, 2013; Daymont and Andrisani, 1984). Regarding the latter, psychological and educational literature finds that academic preparation in math and science are crucial determinants in choosing a quantitative college major; however, there is a gender differences in the effect of academic preparation in math and science on choice of college major and persistency in chosen majors (Eccles, 2007; Trusty, 2002; Ethington and Woffle, 1988). Hanson et al. (1996) argue that women avoid the sciences and mathematics because of inferior prior preparation, lack of innate ability, and biases against women in male-dominated subjects. In their recent work, Card and Payne (2017) find that most of the gender gap in STEM entry can be traced to differences in the rate of high school STEM readiness; less than a fifth is due to gender difference in preference conditional on readiness. Others, however, argue that the small gender differences in math course preparation does not explain the large gender differences in engineering majors (Xie et al., 2003; Kimmel et al., 2012). Women are less likely to major in STEM and more likely to switch out of STEM majors, even after controlling for abilities (Dickson, 2010; Turner and Bowen, 1999; Ahn et al., 2015). Besides that, a growing body of literature suggests that there are fewer women in STEM because they are less confident or more critical of their abilities and more sensitive to negative feedback than men (Roberts, 1991; Johnson and Helgeson, 2002). My paper revisits this question of how much the gender differences in choice of college major can be explained by gender differences in abilities.

2.3 Gender Differences in Choices of Job

Compared to the rich literature on choices of college major and the gender differences in choices of college major, a smaller fraction has been devoted to exploring gender differences in choice of job. Similar to studies about gender differences in major choice, some argue that gender differences in occupational choice are dependent on differences in the distribution of scarce quantitative abilities (Paglin and Rufolo, 1990). Yet minimal research has been done on the career path of STEM college graduates, especially the gender differences in job selection among STEM college graduates. Young women's participation decreases with each stage in the science pipeline with greater gender stratification in science occupations than in science education, which suggests that factors other than training generate inequality in high-status science occupations. The demands of family and children are major nonacademic barriers for women on the pathway to a STEM profession Hanson et al. (1996); Kimmel et al. (2012). Hunt (2016) recently finds that the high exit rate of women leaving STEM fields is driven mostly by female engineers who are dissatisfied with pay and promotion opportunities. She finds that family-related constraints and dissatisfaction with working condition are only secondary factors. In contrast to Hunt (2016), my paper focuses on gender difference in STEM graduates' choice of their first job rather than the gender differences in their career deviations.

3 Data

I use a rich administrative dataset from Purdue Office of the Registrar that tracks the academic records of every Purdue University undergraduate student. The academic records are linked to the First Destination Survey conducted by the Purdue Center for Career Opportunities. The sample includes undergraduate students who graduated between 2005–2014. The data provides individual pre-college information including demographic characteristics; date of enrollment; high school GPA, ACT and SAT subject scores; and applied major.

Table 1 shows some statistics regarding the sample selection. I start with 18904 Purdue graduates; among those, 10,516 have complete information on test scores required by my measurement system. International students make up only 2.3% of this sample. I exclude all of them due to two reasons. First, international students have very distinct educational background compared to the domestic students. Second, I observe only job destination within the U.S., yet most of international students left the U.S. after graduation. The first destination survey is voluntary. I end up with 4,192 graduates who responded to the survey and reported a meaningful job title for their first jobs. Among them, only 3,055 reported a valid annual salary for their first jobs[3].

In total, there are 1,145 women and 1,910 men in this reduced sample, of which 37.03% are women who graduated with a STEM degree while 63.40% are men who graduated with a STEM degree. Among those who graduated with a STEM degree,

[3]With concerns of selection in reporting first job, I estimate the model with a dummy of reporting the first job as a dependent variable and two latent abilities and other characteristics as independent variables. Table B1 shows that women who reported to the survey do not differ on abilities from women who did. Although we see a positive and significant effect on men's extra math ability, the magnitude is too small to have significant economic meaning: one-standar-deviation increase in extra math ability will increase the probability for an average man to report his first job information by 1.5 percentage points.

73.11% of women work in a STEM occupation and 81.17% of men work in a STEM occupation. As Purdue is one of the top engineering schools, it is not surprising that the fractions of both Purdue female STEM graduates and Purdue male STEM graduates are much higher than the fractions in the national-representative survey. Moreover, the gender gap in terms of staying in a STEM field after graduating from a STEM major is much smaller in Purdue data—73.11% and 81.17% for women and men, respectively—than in the national data (26% and 40%).

Table 2 shows the descriptive statistics of the 6 test scores—ACT English, ACT Reading, ACT Math, ACT Science, high school GPA, and grade of COM114[4]—used to identify the two latent abilities in this paper. Overall, women and men have similar test scores, with women having slightly higher ACT English scores, COM114 grades, and high school GPAs while men have slightly higher ACT Reading, ACT Science, and ACT Math scores[5]. Average self-reported annual salary of females is lower than that of males. The Purdue gender wage gap is $8,198.

3.1 STEM Major Definition

I use the "first graduation major" as student's major[6], regardless of what major a student applied to or started with. I observe graduation major for every observation.

[4]Communication 114, Fundamentals of Speech Communication, is a required course for all freshmen at Purdue. It is the study of communication theories as applied to speech, and involves practical communicative experiences ranging from interpersonal communication and small group processes to informative and persuasive speaking in standard speaker-audience situations. https://www.cla.purdue.edu/communication/undergraduate/com_114.html

[5]In the whole sample, there are 41% of students had taken the ACT when they applied to Purdue (including those who also took the SAT). The rest of them took only the SAT. There is no selection on abilities in terms of taking the ACT over the SAT; especially, there is no gender difference in selection on abilities of in terms of taking the ACT over the SAT. Section 4.1 goes into more details about the reason for using ACT scores.

[6]There are 2.76% students who graduated with a double major, and 0.087% students who graduated with a third major. For those who graduated with more than one major, the second and third majors are not considered in this paper. Note that engineering majors cannot be listed as a second major unless the first major is also engineering. A student can not transfer into an engineering major if he or she did not start as an engineering student.

Whoever dropped-out is not included in the sample. All Purdue majors are coded into 6-digit Classification of Instructional Programs (CIP) codes.

The STEM major dummy in this study is defined by the "STEM Designated Degree Program List Effective May 10, 2016" published by U.S. Immigration and Customs Enforcement (ICE, 2016). It is a complete list of fields of study that are considered by the Department of Homeland Security (DHS) to be STEM fields of study for purposes of the 24-month STEM optional practical training (OPT) extension described at 8 CFR 214.2(f)[7]. I categorize all Purdue undergraduate programs showing up on this list as STEM majors and the others as non-STEM majors with some exceptions[8].

3.2 STEM Occupation Definition

The first destination survey provides self-reported first job title, employer (company name), job location (city and state), and annual salary[9].

I match the self-reported job titles to a 6-digit level Standard Occupational Classification (SOC) title with a corresponding SOC code by using O*NET search. I define a self-reported job as a STEM/non-STEM occupation according to the "Detailed 2010 SOC occupations included in STEM"[10] published by the Bureau of

[7]Under 8 CFR 214.2(f)(10)(ii)(C)(2), a STEM field of study is a field of study "included in the Department of Education's Classification of Instructional Programs taxonomy within the two-digit series containing engineering, biological sciences, mathematics, and physical sciences, or a related field.

[8]Some customization has been made according to Purdue's particular programs. "Nursing" is defined as non-STEM degree program by DHS because there are many types of nursing degrees and most of them do not focus on medical training. The nursing major at Purdue offers only Bachelor of Science in Nursing degree, and the placement of undergraduates is basically as registered nurses (RNs). Additionally, a Registered Nurse is defined as a STEM occupation according to BLS. Two two Purdue majors are not documented in the DHS's list: "Radiological Health Sciences" and "Health Sciences General". I treat both as STEM majors based on the degrees both programs offer and the program requirements.

[9]Only 35% of graduates reported full information about their first jobs out of the whole registration record; among those, only 68.76% reported a valid salary (non-missing and non-zero).

[10]There are 840 6-digit SOC occupations and 184 of them are categorized as STEM occupations.

Labor Statistics (BLS, 2012).

4 Model

This general framework is inspired by the Roy model (Roy, 1951), in which individuals make choices to maximize their expected labor outcomes based on their comparative advantages. The core of the empirical strategy follows Carneiro et al. (2003), Hansen et al. (2004), Heckman et al. (2006), Sarzosa and Urzúa (2015), Sarzosa (2017) and Prada et al. (2017). The model captures how college students sort into two groups of majors (STEM majors and non-STEM majors) and, given this path, sort into two groups of occupations (STEM occupations and non-STEM occupations). Particularly, at the start of college, students choose between a STEM major and a non-STEM major; after getting a STEM degree, students choose between a STEM occupation and a non-STEM occupation. Students maximize their expected outcome by making these sequential choices, based on their latent abilities and observable characteristics.

The extended Roy model I implement here can be described as a set of outcome equations linked by a factor structure with two underlying factors[11]: θ^A, the general intelligence and, θ^B, the extra mathematical ability. For each individual, the main outcome variable, annual salary, is given by the following form:

$$Y = \boldsymbol{X_Y}\beta^Y + \alpha^{Y,A}\theta^A + \alpha^{Y,B}\theta^B + e^Y \tag{1}$$

where Y is the outcome variable, $\boldsymbol{X_Y}$ is a vector of all observable controls affecting outcome, β^Y is the vector of returns associated with $\boldsymbol{X_Y}$, $\alpha^{Y,A}$ and $\alpha^{Y,B}$ are the factor loadings of each underlying factor θ^A and θ^B, and e^Y is the error term.

[11] I use “factors” and “latent abilities” interchangeably in the paper.

I assume that e^Y is independent from the observable controls and the unobserved factors, i.e. $e^Y \perp\!\!\!\perp (\theta^A, \theta^B, \boldsymbol{X_Y})$. I further assume that the factors θ^A and θ^B follow the distributions $f_{\theta^A}(.)$ and $f_{\theta^B}(.)$, which both are mixtures of two normal distributions.

Choice of Major. The second model featuring the major choice is a specific case of the model above. For simplicity, I classify choice of college major dichotomously as STEM majors and non-STEM majors, as with the occupation choices. Let D_M^* denotes the net benefit associated with graduating with a STEM degree (relative to a non-STEM degree).

$$D_M^* = \boldsymbol{X_M}\beta^M + \alpha^{M,A}\theta^A + \alpha^{M,B}\theta^B + e^M \tag{2}$$

where $\boldsymbol{X_M}$ is vector of all observable controls affecting major choice, β^M is the vector of coefficients associated with $\boldsymbol{X_M}$, and $\alpha^{M,A}$ and $\alpha^{M,B}$ are the factor loadings. I assume independency of the error term, i.e., $e^M \perp\!\!\!\perp (\theta^A, \theta^B, \boldsymbol{X_M})$. D_M ($= 1$ if $D_M^* > 0$) is a binary variable that equals one if the individual chooses a STEM major and zero otherwise. Thus the major choice model can be re-written as

$$D_M = \mathbb{1}[D_M^* > 0] \tag{3}$$

Choice of Job. After graduating from college, students face the choice between STEM and non-STEM jobs. It is important to note that the major to job flow is not a two by two matrix (STEM major to STEM job, STEM major to non-STEM job, non-STEM major to non-STEM job, non-STEM major to STEM job). According to the Purdue data, only around 3% of the observations falls into the fourth category. I exclude this category for two reasons. First, a STEM job requires certain techniques that are usually obtained in a STEM program and are seldom obtained by one who graduated with a non-STEM degree, in general. Second, due to the small sample size, it is computationally impossible to calculate the model with the fourth category included. Therefore, only graduates with a STEM degree will make a choice between a STEM and a non-STEM job. Non-STEM graduates are considered to work in non-STEM jobs. The job choice model is straightforward:

$$D_J = \mathbb{1}[\boldsymbol{X_J}\beta^J + \alpha^{J,A}\theta^A + \alpha^{J,B}\theta^B + e^J > 0] \text{ if } D_M = 1 \tag{4}$$

where $\boldsymbol{X_J}$ is vector of all observable controls affecting job choice; and β^J, $\alpha^{J,A}$ and $\alpha^{J,B}$ are defined in the same way as in the major choice model. Again, I assume independency of the error term, i.e., $e^J \perp\!\!\!\perp (\theta^A, \theta^B, \boldsymbol{X_J})$. D_J is a binary variable that equals one if the individual chooses a STEM job and zero otherwise, conditional on graduating with a STEM degree ($D_M = 1$).

Now, we can re-define the salary equation (1) in terms of salary from different combinations of choice of major and job. Let Y_{11} denote the salary when $D_M = 1$ and $D_J = 1$ (i.e., choosing a STEM major and a STEM job), and Y_{10} denotes the outcome for those $D_M = 1$ and $D_J = 0$ (i.e., choosing a STEM major and a non-STEM job), and so on. Then we can combine the salary equations and the choices equations to construct a system of outcomes, [Y_{11}, Y_{10}, Y_{00}, D_M, D_J]':

$$Y_{11} = X_Y\beta^{Y_{11}} + \alpha^{Y_{11},A}\theta^A + \alpha^{Y_{11},B}\theta^B + e^{Y_{11}}, \text{ if } D_M = 1, D_J = 1 \tag{5}$$

$$Y_{10} = X_Y\beta^{Y_{10}} + \alpha^{Y_{10},A}\theta^A + \alpha^{Y_{10},B}\theta^B + e^{Y_{10}}, \text{ if } D_M = 1, D_J = 0 \tag{6}$$

$$Y_{00} = X_Y\beta^{Y_{00}} + \alpha^{Y_{00},A}\theta^A + \alpha^{Y_{00},B}\theta^B + e^{Y_{00}}, \text{ if } D_M = 0 \tag{7}$$

$$D_M = \mathbb{1}[\boldsymbol{X_M}\beta^M + \alpha^{M,A}\theta^A + \alpha^{M,B}\theta^B + e^M > 0] \tag{8}$$

$$D_J = \mathbb{1}[\boldsymbol{X_J}\beta^J + \alpha^{J,A}\theta^A + \alpha^{J,B}\theta^B + e^J > 0] \text{ if } D_M = 1 \tag{9}$$

where the error terms $e^{Y_{11}}$, $e^{Y_{10}}$, $e^{Y_{00}}$, e^{M} and e^{J} are assumed to be jointly independent once the unobserved heterogeneity (θ^A and θ^B) is controlled.

I use maximum likelihood estimation (MLE) to estimate the model[12] by integrating the likelihood function below over the distributions of the two factors. The likelihood function is

$$\begin{aligned}
\mathcal{L} &= \prod_{i=1}^{N} \iint \begin{bmatrix} f_{e^{y_{00}}}(X_{Yi}, Y_0 i, \theta^A, \theta^B) \\ \times Pr[D_{Mi} = 0 | X_{Mi}, \theta^A, \theta^B]^{1-D_{Mi}} \times Pr[D_{Ji} = 0 | X_{Ji}, \theta^A, \theta^B]^{1-D_{Mi}} \\ \times f_{e^{y_{10}}}(X_{Yi}, Y_{10} i, \theta^A, \theta^B) \\ \times Pr[D_{Mi} = 1 | X_{Ji}, \theta^A, \theta^B]^{D_{Mi}} \times Pr[D_{Ji} = 0 | X_{Ji}, \theta^A, \theta^B]^{1-D_{Ji}} \\ \times f_{e_{y_{11}}}(X_{Yi}, Y_{11} i, \theta^A, \theta^B) \\ \times Pr[D_{Mi} = 1 | X_{Mi}, \theta^A, \theta^B]^{D_{Mi}} \times Pr[D_{Ji} = 1 | X_{Ji}, \theta^A, \theta^B]^{D_{Ji}} \end{bmatrix} dF(\theta^A) dF(\theta^B) \\
&= \prod_{i=1}^{N} \iint \begin{bmatrix} f_{e^{y_{00}}}(X_{Yi}, Y_0 i, \theta^A, \theta^B) \times \Phi(-\mathcal{M})^{(1-D_{Mi})} \\ \times f_{e^{y_{10}}}(X_{Yi}, Y_{10} i, \theta^A, \theta^B) \times \Phi(\mathcal{M}, \mathcal{J})^{(D_{Mi})(1-D_{Ji})} \\ \times f_{e_{y_{11}}}(X_{Yi}, Y_{11} i, \theta^A, \theta^B) \times \Phi(\mathcal{M}, \mathcal{J})^{D_{Mi} D_{Ji}} \end{bmatrix} dF(\theta^A) dF(\theta^B)
\end{aligned} \tag{10}$$

where $\mathcal{M}$ denotes $(X_{Mi}\beta^M + \alpha^{M,A}\theta^A + \alpha^{M,B}\theta^B)$ and $\mathcal{J}$ denotes $(X_{Ji}\beta^J + \alpha^{J,A}\theta^A + \alpha^{J,B}\theta^B)$.

It is worth noting that I estimate the same model for the female and the male sample separately. The model cannot directly identify the gender difference in ability sorting, i.e., the loading of a presumable interaction term of gender and either factor is not identified.

[12] I use a modified version of the relative developed STATA command, **heterofactor**, by Sarzosa and Urzúa (2016)

4.1 The Measurement System of The Two Latent Abilities

To implement the two-factor model described above, I need to first estimate the distributions of the factors, $F(\theta^A)$ and $F(\theta^B)$, by a measurement system specified based on the nature of the data. The measurement system takes the following form:

$$\boldsymbol{T} = \boldsymbol{X_T}\beta^T + \alpha^{T,A}\theta^A + \alpha^{T,B}\theta^B + \boldsymbol{e^T} \tag{11}$$

where $\boldsymbol{T}$ is a $L \times 1$ vector that contains L test scores associated to latent abilities, θ^A and θ^B. $\boldsymbol{X_T}$ is a matrix with observable controls associated with test scores. $\alpha^{T,A}$ and $\alpha^{T,B}$ are the loadings of the latent abilities. I assume independency of the error terms, $\boldsymbol{e^T} \perp\!\!\!\perp (\theta^A, \theta^B, \boldsymbol{X_T})$. All elements in $\boldsymbol{e^T}$ are mutually independent.

Following the identification strategy of Carneiro et al. (2003), I identify the distribution of two latent abilities, $F(\theta_A)$ and $F(\theta_B)$, and the set of loadings of both abilities in each test score equations, Λ^T from variances and covariances of the residuals from equation system (11). They show that three restrictions have to be fulfilled to identify the factors:

1. Orthogonality of the factors (i.e., $\theta^A \perp\!\!\!\perp \theta^B$);

2. $L \geq 2k + 1$, where L is the number of scores and k is the number of factors;

3. The factor structure within the measurement system needs to follow a triangular pattern, indicating that the first three scores are affected by the first factor only, while the second three scores are affected by both factors.

In order to identify $k = 2$ factors, I will need $L \geq 5$ test scores here. The test scores representing abilities at the beginning of college are listed in (12). The first set of test scores is $ACT_{English}$, $COM114$, and $ACT_{Reading}$; and the second set of test scores is $ACT_{Science}$, $HSGPA$, and ACT_{Math}. The aim of using ACT scores is to gather enough number of test scores to identify two factors. The purpose of identifying two factors is to capture two latent abilities—one representing general abilities and the other representing math-related abilities—and their varying effects on the choices.

$$\boldsymbol{T} = \begin{bmatrix} T_1 \\ T_2 \\ T_3 \\ T_4 \\ T_5 \\ T_6 \end{bmatrix} = \begin{bmatrix} ACT_{English} \\ COM114 \\ ACT_{Reading} \\ ACT_{Science} \\ HSGPA \\ ACT_{Math} \end{bmatrix} \tag{12}$$

The structure of the loadings, $\boldsymbol{\Lambda^T}$, takes the following pattern in (13), where the first factor is allowed to affect all six scores while the second factor is allowed to affect only the scores of $ACT_{Science}$, $HSGPA$, and ACT_{Math}. For example, if a young woman increases her first latent ability, all six of her scores will increase; if she increases her second latent ability, her $ACT_{Science}$, $HSGPA$, and ACT_{Math} wil increase. More specifically, the first factor is identified from the covariances of all six scores; and the second factor is identified form the "leftover" covariances of the second set of scores—$ACT_{Science}$, $HSGPA$, and ACT_{Math}—after the first factor is identified. In this sense, I call the first latent ability as general intelligence, and the second as extra mathematical ability. I assume individuals need "general intelligence" to study and comprehend all subjects.

This is the "triangular" pattern of the loading system mentioned above. Note that $\alpha^{T_3,A}$ and $\alpha^{T_6,B}$ (i.e., the loading of $ACT_{Reading}$ and the loading of ACT_{Math})

are normalized to 1 to facilitate the identification.

$$\boldsymbol{\Lambda^T} = \begin{bmatrix} \alpha^{T_1,A} & \alpha^{T_1,B} \\ \alpha^{T_2,A} & \alpha^{T_2,B} \\ \alpha^{T_3,A} & \alpha^{T_3,B} \\ \alpha^{T_4,A} & \alpha^{T_4,B} \\ \alpha^{T_5,A} & \alpha^{T_5,B} \\ \alpha^{T_6,A} & \alpha^{T_6,B} \end{bmatrix} = \begin{bmatrix} \alpha^{T_1,A} & 0 \\ \alpha^{T_2,A} & 0 \\ 1 & 0 \\ \alpha^{T_4,A} & \alpha^{T_4,B} \\ \alpha^{T_5,A} & \alpha^{T_5,B} \\ \alpha^{T_6,A} & 1 \end{bmatrix} \tag{13}$$

I consider an alternative setting of the factors in Appendix A, which takes the "non-triangular" pattern of the loading system (i.e., each factor is identified only by a different set of test scores). Compared to the preferred specification here, the alternative sacrifices part of the covariances of the test scores by assuming the first factor does not affect the second set of test scores at all.

I use MLE to estimate the measurement system. The likelihood function is:

$$\mathcal{L} = \prod_{i=1}^{N} \iint \begin{bmatrix} f_{e^{T_1}}(X_{Ti}, T_1 i, \gamma^A, \gamma^B)\times \\ \ldots \times f_{e^{T_6}}(X_{Ti}, T_6 i, \gamma^A, \gamma^B) \end{bmatrix} dF(\theta^A) dF(\theta^B) \tag{14}$$

5 Main Results

5.1 Latent Abilities

Tables 3 and 4 show the estimates of the measurement system (11) used to identify the two latent abilities—general intelligence and extra mathematical ability—for women and men, respectively. The set of controls X_T includes the annual state-averaged freshmen graduation rate (AFGR) on the year that each student graduated from high school, home region[13] fix effects and first enrollment semester fix effects[14]. The loadings of general intelligence on all six test scores are significantly positive, meaning that both an increase in general intelligence and an increase in extra mathematical ability will increase the six scores, as expected. Specifically, for example, a one-standard-deviation increase in an average woman's general intelligence will increase her $ACT_{English}$ by 3.94 points and her ACT_{Math} by 2.91 points. A one-standard-deviation increase in an average woman's extra mathematical ability will increase her ACT_{Math} by 2.72 points. Again, one should be cautious when interpreting the estimates of the two latent abilities in this paper. Extra math ability is the factor assumed to be orthogonal to general intelligence. It is measured by the "left over" variations of the test scores—ACT_{Math}, $ACT_{Science}$ and $HSGPA$—after general intelligence is measured. Thus, we should interpret the estimates of extra mathematical ability conditioning on average level of general intelligence.

The predicted distributions of the latent abilities are shown in Figure 1 and Figure 2. They both show that the latent ability distributions are far from normal. Particularly, both female and male general intelligence distribution have a fat right tail. Especially for women, there is an obvious hump on the right tail. This implies the proportion of high-ability women is relatively big, compared to that of men.

[13]The five home regions defined in this paper are the four Census regions—Northeast, South, West, and Midwest—plus Indiana state. I define Indiana as a single region due to the big body of in-state students at Purdue. It is important to have Indiana as a home region itself, because there are many in-state students and they are likely to be different from out-of-state students in educational and family backgrounds.

[14]Table 5 lists the controls in each model and exclusion restrictions.

5.2 The Roy Model

5.2.1 Major Selection

Table 6 shows the effect of abilities on selection between STEM and non-STEM majors. Columns (1) and (2) show the marginal effects of the probit at the means for women and men, respectively. To take into consideration of cohort specific effects, I control for enrollment calendar year fixed effects, enrollment semester fixed effects, degree calendar year fixed effects, degree semester fixed effects, number of graduates in the same major[15] in the same year, and number of female graduates in the same major in the same year.

Both general intelligence and extra mathematical ability are significant determinants of the likelihood of graduating with a STEM degree. Specifically, a one-standard-deviation increase in an average woman's general intelligence will increase her probability of graduating with a STEM degree by 17.16 percentage points; and a one-standard-deviation increase in an average man's general intelligence will increase his likelihood of graduating with a STEM degree by 23.36 percentage points. These estimates are large and statistically significant. The marginal effect of general intelligence on major choice of men is larger than that of their female counterparts. Similarly, extra mathematical ability is an significantly more important determinant on major choice for men than for women. A one-standard-deviation increase in an average man's extra mathematical ability will raise his likelihood of graduating with a STEM degree by 14.02 percentage points; while that number is 9.52 for an average woman.

On average, women sort less on both general intelligence and extra mathematical ability than their male counterparts. Potential explanations could be that, first,

[15] A major is defined by a 6-digit CIP (Classification of Instructional Programs) code.

women are less sensitive to their abilities when making the decision between majoring in STEM and non-STEM fields. I cannot rule out the possibility that they may think they are not good enough for STEM fields. Second, other factors are more dominating for women's major decision, which is consistent with the literature on gender specific preference on college majors. Last, women might be more critical about their abilities or more easily to get discouraged about their performance on coursework (Ahn et al., 2015). Unfortunately, I do not capture the major switching behavior in this study; thus I cannot draw any conclusion about women.

5.2.2 Job Selection

Students who graduated with a STEM degree face the choice between a STEM and a non-STEM job. As mentioned above, I restrict the model to allow only the STEM graduates to choose between the two types of jobs. In this sense, non-STEM graduates are automatically filled in non-STEM jobs. To capture the macroeconomic conditions and job market intensity in a certain year, I control for degree year fixed effects. I include controls for a graduate's home state 's demand for STEM workers (number of STEM occupations in the home state), and home region fix effects, considering that people might take home location into account when making job decision. I also control for total number of Purdue graduates in the same major and number of Purdue female graduates in the same major.

Table 7 shows the marginal effects of latent abilities on probability of working in STEM fields for STEM major graduates. Compared to major selection, both latent abilities are much weaker determinants of the likelihood of working in a STEM job. Specifically, a one-standard-deviation increase in general intelligence for an average female STEM graduate leads to an increase in her likelihood of working in a STEM field by 6.83 percentage points. For an average male STEM graduate, a one-standard-deviation increase in his general intelligence will increase his probability of staying in a STEM field by 4.11 percentage points. The sorting on general intelligence when making job decisions is not statistically different between women and men. Compared to general intelligence, extra mathematical ability is a less important determinant in job decision for STEM graduates. A one-standard-deviation increase in an average female STEM graduate's extra mathematical ability will increase her likelihood of working in STEM by 5.17 percentage points; for men, that increase is 3.21 percentage points[16]. The gender differences in the marginal effects is not statistically significant.

The weak estimates imply that neither female nor male STEM graduates select between STEM and non-STEM job based on their abilities. This is not surprising: given the fact that they have already graduated with a STEM degree, they should be similarly qualified for a STEM job. One may ask, why would students who received a STEM degree not want to enter STEM occupations? What makes STEM graduates deviate from their original choices? More analysis of job selection determinants appears in Section 6.

5.2.3 Salary

Tables 8 and 9 show the salary returns to abilities for male and female who endogenously sort into different majors and jobs[17]. Columns (1) to (3) in each table present the coefficients of interest for three types of men/women—graduating with a STEM degree and working in a STEM field, graduating with a STEM degree and working in a non-STEM field, and graduating with a non-STEM degree and working in a non-STEM field—respectively. For simplicity, I denote these three types of

[16] Note that the small estimates of the extra mathematical ability are probably due to the small variations that the factor captures. We cannot interpret these small estimates as that the mathematical ability is not important in choices between STEM and non-STEM.

[17] The full table of estimates is in Appendices B4, B5, and B6.

men as $Male_{11}$, $Male_{10}$, and $Male_{00}$; the same holds for women. I control for state-level annual unemployment rate, job region fixed effects[18], yearly national number of graduates, yearly national number of graduates in STEM, yearly national number of female graduates, yearly national number of female STEM graduates, yearly national fraction of STEM employment in total employment, and yearly national employment in STEM and non-STEM fields.

In general, both general intelligence and extra mathematical ability have positive returns to salary for all three types of women and men. Women are more rewarded for both of their abilities then men, comparing the magnitude of the estimates. One thing to note is that all types of women—$Female_{11}$, $Female_{10}$ and $Female_{00}$—are rewarded for their extra mathematical ability. For an average woman who graduates with a non-STEM degree and works in a non-STEM job, a one-standard-deviation increase in her extra mathematical ability will increase her annual salary by $2,474. In contrast, $Male_{00}$ has no significant return on extra mathematical ability. This can be one explanation that why women are less likely to enroll in STEM major: women with high extra mathematical ability are more rewarded outside of STEM field than men are. It suggests that women should invest in extra mathematical ability.

Comparing within gender, $Male_{10}$ and $Male_{00}$ have smaller salary returns to general intelligence than do $Male_{11}$. However, those estimates are not statistically different from each other. $Female_{11}$ and $Female_{10}$ have significantly higher returns to general intelligence than $Female_{00}$, again suggesting that high-ability women should major in STEM.

[18] I defined 10 job regions according to the Census regional devisions: "New England", "Mid-Atlantic", "East North Central", "West North Central", "South Atlantic", "East South Central", "West South Central", "Mountain", "Pacific", and "Indiana". Again, it is important to have Indiana as a regional devision here due to the large body of in-state students; and a large fraction of them will hold in-state jobs after graduation.

5.2.4 Model Fit

Table 11 shows that the model fits the actual data well, with respect to the test scores. Both the first and second moments are very close to the data. Figures 7 and 8 show the cumulative distributions of the test scores and the predicted test scores for male and female, respectively. Generally speaking, both gender's predicted test scores fit very well with the actual data. The data for high school GPA and communication 114 grade points are lumpy because these two variables are discrete. Tables 10 presents evidence on the models' goodness-of-fit on the first and second moments of major choice (D_M), job choice (D_J) and salary ($Salary_{11}$, $Salary_{10}$, and $Salary_{00}$). They are product of 1,000,000 simulations of the model based on bootstrapping 1000 times from the estimates and 1000 random draws from the factor distributions within each bootstrap. Comparing the "Data" and the "Model Prediction" shows that the model accurately predicts the means and standard deviations for each outcome of both genders. This finding provides confidence about the fact that the counterfactuals predicted by the model are appropriate.

5.3 The Distributions of Abilities of the Three Career Paths

To reveal the link between latent abilities and the endogenous choices between STEM and non-STEM major and job, I construct Figure 3–Figure 6. Figure 3 presents the distributions of general intelligence of $Male_{00}$, $Male_{10}$, and $Male_{11}$, from the left to the right. All three distributions are far from normal. Comparing $Male_{00}$ to the other two shows that men with a STEM degree have significantly higher general intelligence than men with a non-STEM degree. In particular, the distributions of both $Male_{10}$ and the $Male_{11}$ have slight humps on the right tails, indicating that men with relatively high general intelligence sort into STEM majors.

Figure 4 shows the distributions of extra mathematical ability of the three categories of men. Similarly, the distribution of $Male_{00}$ is apart from the distributions of $Male_{10}$ and $Male_{11}$, indicating men with high extra mathematical ability are more likely to be majoring in STEM.

Women's sorting behavior in major decision is surprisingly different from men's. Figure 5 shows general intelligence distributions of $Female_{00}$, $Female_{10}$, and $Female_{11}$. Remarkably, high-ability women are more likely to major in non-STEM fields than their male counterparts. The significant hump on the right tail of the distribution of $Female_{00}$ suggests that a mass of women with high general intelligence graduate with non-STEM majors. We do not see this shape in the distribution of $Male_{00}$. Moreover, there is little evidence of sorting on extra mathematical ability among women: the three distributions in Figure 6 are equally far apart from each other. This pattern suggests that extra mathematical ability is a weaker determinant for women to make major decisions than men.

Overall, the different sorting behaviors in major decisions between men and women revealed by the ability distributions mirrors my findings in Table 6; that is, on average, men sort more on both abilities than women. Furthermore, women of every level of ability are less likely to major in STEM fields or work in STEM fields than their male counterparts. Evidence is provided by Table 12 and 13, which show the predicted values of majoring in STEM fields (working in STEM fields) by general intelligence deciles and extra mathematical ability deciles, respectively. We see that women's probability of majoring in STEM fields (Panel A) or probability of working in STEM fields (Panel B) is smaller than men's from ability decile 1 to decile 10. Moreover, the gender differences on the right tail of the ability distribution is slightly larger. High-ability (right tail) women seem to be "ignoring" or misreading their abilities when making major decisions. This is very interesting but not surprising:

one potential explanation comes from the literature about women being too critical about their skills and less confident relative to men (Ahn et al., 2015). Furthermore, the fact that the distributions of 10 and 11—for both genders—are close to each other suggests that neither men nor women sort greatly on abilities when making job decisions, which is consistent with the estimates in Table 7.

6 Counterfactuals

6.1 The Effect of Majoring in STEM

To understand the effect of majoring in STEM fields, I calculate the average treatment effect (ATE) of majoring in STEM fields for women and men, respectively:

$$ATE_M = E[Y_{10} - Y_{00}|\theta, x]$$

where the treatment is majoring in STEM, noted as subscript M. Panel A in Table 14 shows the averaged ATE of majoring in STEM over the whole distribution of ability. An average female majoring in a non-STEM field and working in a non-STEM field would have earned \$7,171 more if she had majoried in a STEM field and worked in a non-STEM field. That number is \$7,312 for an average male. On average, there is no gender differences in the ATE of majoring STEM fields.

To show the variation of ATE across the ability distribution, I calculate ATE for each ability decile. Figure 9 shows the ATE of majoring in STEM fields for both genders over the deciles of f_1, general intelligence. Similarly, Figure 10 shows the ATE of majoring in STEM fields for both genders over the deciles of f_2, extra mathematical ability. Both curves on the left and right panels are upward sloping, indicating positive returns to abilities. There is barely any gender differences on the level of ATE for majoring in STEM fields. Females' ATEs over both ability distributions have slightly larger standard deviations, implying that among individuals with the same ability, females' returns to a STEM degree varies more than males'.

To capture the counterfactuals for individuals on the margin of the treatment, I calculate the marginal treatment effect (MTE) of majoring in STEM fields for female and male, respectively.

$$MTE_i = E[Y_{10} - Y_{00} | Pr(X_{M,i}\beta^M + \alpha^{M,A}\theta_i^A + \alpha^{M,B}\theta_i^B = e_i^M) = 1]$$

where MTE_i is the treatment effect of majoring in STEM for individuals who are indifferent of majoring in STEM, having observable characteristics $X_{M,i}$, and unobserved abilities θ_i^A and θ_i^B.

Figure 11 and Figure 12 present the MTE of majoring in STEM for both genders across the deciles of general intelligence and math ability. In general, MTEs are upward sloping, except males' MTE across general intelligence ability (the right panel of Figure 11, which is insignificantly downward slopping. Comparing the ATEs of majoring in STEM fields (Figure 9 and Figure 10) and the MTEs of majoring in STEM fields (Figure 11 and Figure 12) shows that they are very similar except that the MTEs have significant larger standard deviations. This probably occurs for two reasons: we are comparing fewer individuals on the margin within the same ability deciles; and the observable characteristics of an individual on the margin vary a lot more than an average individual.

6.2 The Effect of Working in STEM

In the Section 5.2.2, I discuss the fact that women are less likely to stay in STEM fields after they graduated with a STEM degree and argue that it is not due to gender differences in ability sorting. The next question is, "how much do people lose by opting out of STEM fields after getting STEM degrees?" To answer that, I calculate the ATE of having a STEM job relative to having a non-STEM job for those who graduated with a STEM degree.

$$ATE_J = E[Y_{11} - Y_{10}|\theta, x, D_M = 1]$$

Panel B in Table 14 shows the averaged ATE of working in a STEM job over the whole ability distribution. For a woman who is picked at random from the sample of women who graduated with a STEM degree, working in a STEM job would increase her annual salary by \$6,480 over working in a non-STEM job. Although this number is not extraordinarily large, compared to male's averaged ATE, \$2,612, the effect of working in STEM for an average female STEM graduate is significantly larger than that of her male counterpart.

Figure 13 and Figure 14 also shows that a female's ATE of working in a STEM job is larger than a male's across deciles of both abilities. One may notice that the ATE is downward-sloping across deciles of extra mathematical ability. This is due to the fact that the salary return to extra mathematical ability for group 10 (STEM degrees and non-STEM jobs) is higher than that for group 11 (STEM degrees and STEM jobs). This implies that the returns to working in STEM is positive across the entire distribution of extra mathematical ability; but with a declining marginal return.

Again, I present the MTE of working in STEM, which can be written as follows:

$$MTE_i = E[Y_{11} - Y_{10}|Pr(X_{J,i}\beta^J + \alpha^{J,A}\theta_i^A + \alpha^{J,B}\theta_i^B = e_i^J) = 1, D_M = 1]$$

Figure 15 and Figure 16 depict the marginal treatment effect of working in

STEM for each gender over the deciles of each abilities. The trends look similar to the figures of the ATEs above. However, a female's MTE of working in a STEM job at each ability decile is slightly larger than female's ATE of working in a STEM job. Yet this pattern is not true for the males. Additionally, we can see the gender differences in the MTE of working in STEM as in the ATE. A male's MTE of majoring in STEM is significantly lower than that of a female, suggesting that the effect of working in STEM for females who are on the margin is significantly larger than that of their male counterparts.

6.3 The Effect of Majoring and Working in STEM

$$ATE_M = E[Y_{11} - Y_{00}|\theta, x]$$

Now I compare two groups, one working in STEM jobs with STEM degrees, the other working in non-STEM jobs with non-STEM degrees. This is the counterfactural of working in STEM for those who do not have STEM degrees. Generally speaking, an average woman is more rewarded than an average man for majoring in STEM, revealing by Panel C in Table 14. Specifically, an average woman who is picked at random from the entire female sample would earn $13,651 more annually if she works in a STEM job with a STEM degree rather than works in a non-STEM job with a non-STEM degree. That number is only $9,925 for an average man, which is statistically lower. It is important to notice that there is no gender differences in treatment effect for majoring in STEM fields; and the gender differences of treatment effect for working in STEM fields is close to the gender differences in treatment effects to majoring and working in STEM fields. Thus, to sum up, on average, both women and men have positive treatment effects from majoring and working in STEM, and the gender differences in treatment effect for majoring in STEM fields can be attributed to gender differences in rewards for a STEM jobs.

Figure 17 and Figure 18 show the ATE of majoring and working in STEM fields across ability deciles. Again, the level of a female's ATE are above the level of a male's ATE, indicating that women are more rewarded for majoring and working in STEM fields. Ironically, the fact is that women are less likely to major in STEM fields and more likely to opt out.

6.4 Foregone Earnings of the High-Ability Women and the Gender Wage Gap

Having seen the effect of majoring and working in STEM fields by ability deciles, I argue that high-ability women could have earned a lot more had they earned a STEM degree and worked in STEM. Recall the simulated general intelligence distribution of $Female_{00}$ group in Figure 5. Compared with $Male_{00}$ group in Figure 3, $Female_{00}$ has a lump on the right tail, implying that high-ability women are less likely to majoring in STEM than high-ability men. To quantify the total losses in terms of salary for high-ability non-STEM women, I integrate the average treatment effect of majoring in STEM over the shadowed area on Figure 19. This area is created by the interaction of the general intelligence distribution of $Male_{00}$ with that of $Female_{00}$, where there is a mass of the women distributed on the hump-shaped region of the general intelligence distribution of $Female_{00}$. Assuming that high-ability women act like high-ability men when making college major decisions (i.e. the individuals distributed on the right tail of general intelligence distribution of $Female_{00}$ are like that of $Male_{00}$), how much annual income would they gain?

The value generated by the shadowed area is \$772, which explains 9.42% of the gender wage gap. The gender wage gap, \$8,198, is calculated by subtracting the Purdue female graduates' average annual salary from the Purdue male graduates' average annual salary. Although 9.42% is not a gigantic number at the first glance, one should not take it for granted: the 9.42% of the gender wage gap is contributed only by the high-ability women who make up the mass on the right tail of $Female_{00}$ distribution; those high-ability women make up only 5.60% of the Purdue female sample. Thus, one should not interpret the result as every woman gains \$772 per year by majoring in STEM fields, which is clearly minuscule. Instead, the 9.42% is all attributed to the 5.60% of high-ability women, who are most likely to be capable of majoring in STEM; each of them would have gained about \$13,000–\$20,000 per year.

6.5 Counterfactuals of Major Choice

Now let us get back to the question of why women are less likely to major in STEM than men. From the estimates in Table 6, we see that women and men sort on abilities differently when choosing college majors. What if women had sorted the same as men? What if women and men had the same distributions of abilities? Table 15 presents the results of counterfactual analysis on the likelihood of majoring in STEM, following the approach in Urzua (2008). The first row displays the model predicted proportion of graduates with a STEM major for females and males, respectively. For clarity, I write out the expressions as follows: $D_M^f(\beta^{M,f}, X_M^f, \alpha^{M,A,f}, \alpha^{M,B,f}, \theta^{A,f}, \theta^{B,f})$ and $D_M^m(\beta^{M,m}, X_M^m, \alpha^{M,A,m}, \alpha^{M,B,m}, \theta^{A,m}, \theta^{B,m})$, where superscripts denote the gender.

The second row answers the question of what if women had sorted on abilities the same as men. It shows that 37.49% of women would graduate in STEM when women are assumed to have the the same factor loadings as men ($D_M^f(\beta^{M,f}, X_M^f, \alpha^{M,A,m}, \alpha^{M,B,m}, \theta^{A,f}, \theta^{B,f})$). The third row answers the question about what if women have had men's abilities. It shows women's proportion of graduates in STEM increases to 39.58% when women are assumed to have the same ability distributions as men ($D_M^f(\beta^{M,f}, X_M^f, \alpha^{M,A,f}, \alpha^{M,B,f}, \theta^{A,m}, \theta^{B,m})$).

Furthermore, by assuming that women had both the same abilities and the same loadings of abilities, the proportion of graduates in STEM would be 40.37%. These counterfactuals indicate that women would be slightly more likely to major in STEM fields, or the gender differences in fraction of majoring in STEM fields would have shrunken, had they possessed the same ability distributions or evaluated their abilities in the same way as men; however, the changes are not statistically different from the factual.

Giving that the gender differences in major choice is not primarily due to gender differences in the latent abilities or the sorting on abilities, I conduct the similar exercises on the observables. If we substitute men's coefficients of the observables for women's ($D^f_M(\beta^{M,m}, X^f_M, \alpha^{M,A,f}, \alpha^{M,B,f}, \theta^{A,f}, \theta^{B,f})$), the proportion of female majoring in STEM would have significantly increased to 42.53%. Substituting men's observable variables for women's, we get the proportion of female majoring in STEM as 57.63%. Given both male's observable variables and the corresponding coefficients to women, the counterfactual estimate increases even more. Thus, the counterfactuals in Row 5–Row 7 suggest that gender differences in choosing major can be primarily attributed to observable characteristics, including economic conditions, labor demand for STEM workers, and cohort effects. Besides these, there is still unexplained gender gap in major choice, which could be due to unobserved personal preferences. Those unobserved gender-specific personal preferences are more dominating when women choose their college majors, as shown in the literature.

6.6 Counterfactuals for Job Choice

The weak determinants in the job model imply that neither men nor women select much between a STEM and a non-STEM job based on their abilities. This finding is very interesting, given the fact that they have already graduated with STEM degrees. Another question this paper intends to answer is why female STEM graduates choose different jobs than their male counterparts. Given that it is not due to the differential sorting behavior on abilities from the results shown in Table 7, no wonder that substituting women's latent abilities or returns to abilities with men's does not close the gender gap in job decision (see Row 2–Row 4 in Table 16). I then seek answers from the gender differences in the observable characteristics.

To do so, I show the proportion of female STEM workers in female STEM graduates when compensating them with men's returns to the observable characteristics ($D_J^f(\beta^{J,m}, X_J^f, \alpha^{J,A,f}, \alpha^{J,B,f}, \theta^{A,f}, \theta^{B,f})$). Row 5 in Table 16 shows that women would have been more likely to stay in STEM fields if we assume that they had the same returns to the observable characteristics as men. In particular, there would be 75.12% female STEM graduates staying in STEM fields, instead of the factual, 70.05%. This 5 percentage points increase explains 41.5% of gender gap in STEM graduates' choosing between a STEM job and a non-STEM job. The implication here is similar to the counterfactual analysis on major decision: gender differences in job choices among STEM graduates can be explained by gender differences in the coefficient of the observables but not the unobserveds.

After a full decomposition of the predictors in the job selection model, I find that the region where one is from is a major factor for female STEM graduates and their decision to pursue a STEM or non-STEM job. In Table 17, Column (1) shows the counterfactuals of excluding the each variable, and Column (2) shows the counterfactuals of substituting each women's coefficient with men's. Substituting women's home region fixed effects with men's, the gender gap on job choice is fully closed. Additionally, none of the other predictors significantly explains the gender gap. The potential mechanism is very interesting: there may be a trade-off between a non-STEM job in the home state and a high-paying STEM job opportunity away from the home state for female STEM graduates. Table 18 also shows supportive evidence: those who go back to their home state are more likely to opt out of STEM fields.

This finding suggests an potential explaination for the previous question about why STEM graduates changed their minds after getting a STEM degree. STEM graduates updated their beliefs about job characteristics including job location, work environment, etc. during their job search. When students chose their college major, some of the job characteristics were not concerns, e.g., whether the job locates in the same state of her home state. This finding sheds new light on the studies about the career choices of female STEM graduates and even on the broader topic of women's career choices.

7 Policy Implications

A possible policy implication of the findings in this paper is to encourage programs or activities that improve the awareness of high school girls of their own abilities. Transcripts of SATs and ACTs informs high school students about their percentile rankings in these standardized tests, which indicate how they did compared to everyone else. However, that is not informative enough for choosing college majors. High school students and their parents may not know what those scores and percentile rankings mean in terms of potential career paths.

The Career Mapping Visualization System created by a research group[19] has made a visualization tool to help high school students understand the requirements for graduating from a certain major and the requirements for each occupation[20]. This tool helps high school students, parents, and high school teachers to com-

[19] Lilly Endowment for "Transforming Indiana into a Magnet for High Technology Jobs".
[20] https://va.tech.purdue.edu/careerVis/

prehend the requirements for each career path and each student's amount of the expected abilities relative to peers as well as to have appropriate expectations about career outcomes.

Also, it is crucial to make high school girls more informed about the returns to a STEM education. It is costly to train students to be "ready" for STEM, so why do we not attract the "already-ready" ones—the high-ability women in this study—to major in STEM? Considering how much money the high-ability women would have made, we should encourage state-funded program designed to attract high-ability high school girls to STEM majors. One example is a state-funded program for campus visits by middle or high school girls, for instance, Girl Day at UT Austin[21].

8 Conclusion

This paper investigates the gender differences in ability sorting in choices of college majors and jobs by applying an extended Roy model of unobserved heterogeneity to explore the endogenous sequential decisions: the choice between a STEM and a non-STEM major and the choice between a STEM and a non-STEM job. I find that women sort less on abilities when choosing majors; and high-ability women are more likely to choose non-STEM majors than men. By majoring in non-STEM majors, high-ability women give up as much as $13,000–$20,000 in annual salary, which in total explains about 9.4% of the gender wage gap.

There are several potential explanations for this sorting behavior among high-ability women. I cannot rule out the possibility that they may think they are not skilled enough for STEM. Additionally, they may not be well informed about the pecuniary value of the career paths associated with their abilities. The policy implication in Section 7 comments on both of the potential reasons. Alternatively,

[21] https://girlday.utexas.edu

those high-ability women are well aware of their own abilities and informed about the great returns to STEM education and STEM careers, but intentionally choose the non-STEM career path to have the nonpecuniary value of pursuing their ideal but lower-paying jobs or caring for family, as suggested in the literature. In this case, we should consider the annual income loss quantified in my paper is the minimum gain of these women.

Another contribution of this paper is to affirm that the gender gap on job choice is due *not* to different sorting on abilities, but to other observable or unobserved characteristics. Home region is important in the job decisions for women; women STEM graduates who return to their home state are more likely to opt out of STEM fields. The future research should investigate the effect of family on female STEM graduates' job choice and seek answers for whether they are going back home for a familiar social networks, marriage, or access to child care.

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Table 1: Sample Selection

Sample	**Total**	**Female**	**Male**
All	18,904	8,763	10,141
Six Scores Complete	10,516	4,682	5,834
Six Scores Complete (Domestic Student)	10,282	4,565	5,640
First Destination Survey Complete	4,192	1,687	2,505
Valid Self-Reported Salary	3,055	1,145	1,910

Note: The sample includes undergraduate students graduated between 2005–2014. Six scores are: ACT English, ACT Reading, ACT Science, ACT Math, grade points of Communication 114 (required for all Purdue freshmen) and high school GPA. A valid self-reported salary means the graduate self-reported a positive annual salary.

Table 2: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Panel A. Females					
ACT_English	25.661	4.617	11	36	1145
COM114 grade points	3.526	0.570	1	4	1145
ACT_Reading	25.940	4.944	12	36	1145
ACT_Science	24.668	3.960	12	36	1145
HS_GPA	3.532	0.426	2	4	1145
exp(HS_GPA)	36.971	13.043	7.389	54.598	1145
ACT_Math	25.645	4.517	15	36	1145
Self-reported Annual Salary	45179.963	14365.635	8000	101000	1145
STEM Major	0.370	0.483	0	1	1145
STEM Job	0.271	0.445	0	1	1145
STEM Major, STEM Job	0.731	0.444	0	1	424
Panel A. Males					
ACT_English	25.507	4.640	11	36	1910
COM114 grade points	3.339	0.630	1	4	1910
ACT_Reading	26.278	4.951	8	36	1910
ACT_Science	26.730	4.398	11	36	1910
HS_GPA	3.483	0.427	2	4	1910
exp(HS_GPA)	35.290	12.868	7.389	54.598	1910
ACT_Math	28.237	4.185	15	36	1910
Self-reported Annual Salary	53427.169	13178.711	5250	107000	1910
STEM Major	0.634	0.482	0	1	1910
STEM Job	0.516	0.5	0	1	1910
STEM Major, STEM Job	0.812	0.391	0	1	1211

Note: The sample includes undergraduate students graduated from 2005–2014. Standard test of ACT English, ACT Reading, ACT Science, and ACT Math have minimum of 0 and maximum of 36. COM114 grade points range from 2-4. Whoever fail the class (grade points less than 2) has to re-take the class in order to graduate; and I do not observe dropouts. "exp(HS_GPA)" is the exponential of high school GPA, which is used in the estimation instead of HS_GPA. Self-reported Annual Salary is nominal and in USD.

Table 3: Identification of Abilities at College Entrance, Female

Dependent Var	ACT_E	COM114	ACT_R	ACT_S	HSGPA	ACT_M
Home Region: Indiana	-0.569	-0.128	-0.660	-1.209***	1.889	-0.801
	(0.773)	(0.094)	(0.827)	(0.449)	(1.832)	(0.510)
Home Region: Midwest	1.044	-0.171*	0.210	-0.201	-3.313*	0.335
	(0.783)	(0.099)	(0.853)	(0.477)	(1.946)	(0.547)
Home Region: Northeast	-1.389	-0.260*	-0.893	-0.897	-1.779	0.0322
	(1.158)	(0.147)	(1.264)	(0.709)	(2.892)	(0.797)
Home Region: South	2.594**	-0.073	1.918*	1.141**	2.550	1.839***
	(1.066)	(0.120)	(1.108)	(0.573)	(2.334)	(0.656)
AFGR	0.122***	0.013**	0.103**	0.113***	0.566***	0.111***
	(0.039)	(0.005)	(0.043)	(0.0255)	(0.103)	(0.030)
First Term Semester: Fall	2.042*	-0.112	2.557*	1.550*	8.124**	2.827**
	(1.084)	(0.178)	(1.327)	(0.942)	(3.727)	(1.306)
First Term Semester: Spring	-1.536	-0.050	0.597	-1.167	-4.794	-1.524
	(1.552)	(0.258)	(1.905)	(1.301)	(5.257)	(1.648)
General Intelligence	1.127***	0.045***	1	0.771***	1.780***	0.832***
	(0.020)	(0.005)	X	(0.025)	(0.097)	(0.029)
Extra Math Ability				0.361***	1.199***	1
				(0.043)	(0.161)	X
Constant	14.043***	2.754***	15.706***	15.13***	-13.83	14.54***
	(3.088)	(0.427)	(3.486)	(2.128)	(8.585)	(2.620)
Observations	1,145					

Note: Each column is a separate regression specified in Equation 11. All columns have the same observations: 1145. The loading of General Intelligence is normalized to one in regression of $ACT_{Reading}$, so that General Intelligence takes the metrics of $ACT_{Reading}$. The loading of Extra Mathematical Ability is normalized to one in regression of ACT_{Math}, so that Extra Mathematical Ability takes the metrics of ACT_{Math}. I control for annual state-averaged freshmen graduation rate (AFGR) on the year of each student graduated from high school, home census region fixed effects and first enrollment semester fix effects.

Table 4: Identification of Abilities at College Entrance, Male

	ACT_E	COM114	ACT_R	ACT_S	HSGPA	ACT_M
Home Region: Indiana	-2.216***	-0.071	-1.981***	-1.831***	-0.180	-1.388***
	(0.687)	(0.080)	(0.703)	(0.397)	(1.437)	(0.394)
Home Region: Midwest	-0.995	-0.206**	-1.111	-0.427	-5.342***	-0.267
	(0.736)	(0.085)	(0.748)	(0.421)	(1.519)	(0.421)
Home Region: Northeast	-1.441	-0.204*	-1.138	-0.290	-3.640*	-0.415
	(0.978)	(0.119)	(1.013)	(0.577)	(2.120)	(0.536)
Home Region: South	0.0362	-0.013	-0.068	0.188	-0.141	0.704
	(0.742)	(0.093)	(0.777)	(0.479)	(1.699)	(0.518)
AFGR	0.169***	0.019***	0.089**	0.108***	0.654***	0.124***
	(0.031)	(0.004)	(0.034)	(0.0224)	(0.0810)	(0.0226)
First Term Semester: Fall	4.941***	0.210	3.610**	5.844***	13.67***	6.089***
	(1.011)	(0.179)	(1.237)	(0.853)	(3.228)	(0.670)
First Term Semester: Spring	2.794**	-0.232	1.270	4.297***	10.26**	4.402***
	(1.315)	(0.225)	(1.578)	(1.110)	(4.100)	(1.019)
General Intelligence	1.151***	0.045***	1	0.831***	1.557***	0.729***
	(0.017)	(0.004)	X	(0.022)	(0.078)	(0.021)
Math Ability				0.455***	1.107***	1
				(0.029)	(0.103)	X
Constant	9.045***	2.204***	17.235***	13.607***	-25.932***	13.383***
	(2.582)	(0.379)	(2.880)	(1.888)	(6.891)	(1.810)
Observations	1,910					

Note: Each column is a separate regression specified in Equation 11. All columns have the same observations: 1910. The loading of General Intelligence is normalized to one in regression of $ACT_{Reading}$, so that General Intelligence takes the metrics of $ACT_{Reading}$. The loading of Extra Mathematical Ability is normalized to one in regression of ACT_{Math}, so that Extra Mathematical Ability takes the metrics of ACT_{Math}. I control for annual state-averaged freshmen graduation rate (AFGR) on the year of each student graduated from high school, home census region fixed effects and first enrollment semester fix effects.

Table 5: Observed Controls in Each Model (Exclusion Restrictions)

Variables	Controls			
	X_T	X_M	X_J	X_Y
Averaged Freshmen Graduation Rate (AFGR)	Yes			
First Enrollment Year Fixed Effects		Yes		
First Enrollment Semester Fixed Effects	Yes	Yes		
Home (Census) Region Fixed Effects	Yes		Yes	
Degree Year Fixed Effects		Yes	Yes	
Degree Semester Fixed Effects		Yes	Yes	
# Purdue Graduates in Same Major		Yes	Yes	
# Purdue Female Graduates in Same Major		Yes	Yes	
State-level STEM Employment			Yes	
STEM Fraction of Total Employment				Yes
# STEM Total Employment				Yes
# nonSTEM Total Employment				Yes
# Total Graduates				Yes
# STEM Major Graduates				Yes
# Female Graduates				Yes
# Female STEM Major Graduates				Yes
State Annual Unemployment Rate				Yes
Job Location Region Fixed Effects				Yes

Table 6: Likelihood of Graduating with A STEM Major

	(1) Female	(2) Male
	Marginal Effects at the Mean	
General Intelligence	0.048***	0.066***
	(0.0058)	(0.0056)
Extra Math Ability	0.034***	0.049***
	(0.0084)	(0.0063)
N	1145	1910

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$

Note: Column (1) and column (2) show the marginal effect of probit at the means for the female and male sample, respectively. All marginal effects reflect to changes in probability of graduating in STEM with one unit increase in the corresponding ability. The standard deviation of female's and male's General Intelligence is 3.576 and 3.539; the standard deviation of female's and male's Extra Mathematical Ability is 2.801 and 2.862. The dependent variable in both column (1) and (2) is dummy of majoring in STEM. Number of Purdue graduates in the same major, number of Purdue female graduates in the same major, first enrollment year, first enrollment semester, degree year fixed effects are controlled but not shown in this table for short. See Table B2 for the full table. The factor loadings are also shown in the full table.

Table 7: Likelihood of STEM Graduates Work in STEM Occupations

	(1) Female	(2) Male
	Marginal Effects at the Mean	
General Intelligence	0.0191*	0.0116**
	(0.0109)	(0.0059)
Mathematical Ability	0.0190	0.0116*
	(0.0159)	(0.0070)
N	1145	1910

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$

Note: Column (1) and column (2) show the marginal effect of probit at the means for the female and male sample, respectively. All marginal effects reflect to changes in probability of working in STEM with one unit increase in the corresponding ability of STEM graduates. The standard deviation of female's and male's General Intelligence is 3.496 and 3.349; the standard deviation of female's and male's Extra Mathematical Ability is 2.723 and 2.771. The dependent variable in both column (1) and (2) is dummy of majoring in STEM. Number of Purdue graduates in the same major, number of Purdue female graduates in the same major, home state STEM demand, degree year fixed effects, home region fixed effects are controlled but not shown in this table for short. See Table B3 for the full table. The factor loadings are also shown in the full table.

Table 8: Salary for Males

VARIABLES	(1) $Salary_{11}$	(2) $Salary_{10}$	(3) $Salary_{00}$
Unemployment Rate at Job State	-838.5**	-1,059	-143.3
	(357.7)	(883.3)	(575.4)
STEM Employment Fraction	-178,101	-2.582e+06	-51,061
	(1.719e+06)	(4.308e+06)	(2.321e+06)
# Employment in STEM Occupations	-0.000123	0.0257	0.00205
	(0.0141)	(0.0360)	(0.0190)
# Employment in nonSTEM Occupations	-3.45e-05	-0.000972	-5.34e-05
	(0.000584)	(0.00149)	(0.000789)
# Graduates	1.208*	2.879	0.130
	(0.663)	(1.764)	(0.932)
# STEM Major Graduates	-1.200	-3.630	-1.450
	(1.278)	(2.982)	(1.795)
# Female Graduates	-2.124	-6.176	-0.834
	(1.524)	(3.882)	(2.114)
# Female STEM Major Graduates	2.515	10.05	4.488
	(3.606)	(8.119)	(4.967)
General Intelligence	422.7***	156.1	172.7
	(129.1)	(343.3)	(175.4)
Mathematical Ability	716.3***	1,102***	303.6
	(160.3)	(374.5)	(192.7)
Constant	58,383	454,814	182,691
	(116,660)	(313,697)	(159,320)
Observations	1,910		

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Note: Column (1)–(3) separately show the estimates for men who graduate in STEM and work in STEM ($Salary_{11}$), men who graduate in STEM and work in non-STEM ($Salary_{10}$), and men who graduates in non-STEM and work in non-STEM ($Salary_{00}$). The dependent variable in all columns is annual salary in USD. Census region of job fixed effects are included but not shown. See full set of results in Table B4, Table B5, and Table B6.

Table 9: Salary for Females

VARIABLES	(1) $Salary_{11}$	(2) $Salary_{10}$	(3) $Salary_{00}$
Unemployment Rate at Job State	-134.2	241.1	-998.8
	(619.7)	(1,577)	(614.0)
STEM Employment Fraction	-3.019e+06	-2.606e+06	-2.052e+06
	(2.969e+06)	(7.243e+06)	(2.284e+06)
# Employment in STEM Occupations	0.0177	0.0240	0.0140
	(0.0241)	(0.0597)	(0.0190)
# Employment in nonSTEM Occupations	-0.000925	-0.000850	-0.000669
	(0.00100)	(0.00248)	(0.000786)
# Graduates	1.090	0.333	0.966
	(1.858)	(1.778)	(1.002)
# STEM Major Graduates	0.480	1.015	-0.749
	(3.639)	(2.448)	(1.670)
# Female Graduates	-1.460	-0.488	-1.561
	(4.362)	(3.534)	(2.129)
# Female STEM Major Graduates	-1.776	-2.775	1.300
	(10.32)	(6.050)	(4.369)
General Intelligence	779.0***	310.3	154.7
	(218.4)	(418.4)	(158.2)
Mathematical Ability	932.5***	1,513**	888.6***
	(320.6)	(600.8)	(216.1)
Constant	16,546	202,269	75,694
	(289,424)	(385,859)	(158,521)
Observations	1,145		

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Note: Column (1)–(3) separately show the estimates for women who graduate in STEM and work in STEM ($Salary_{11}$), women who graduate in STEM and work in non-STEM ($Salary_{10}$), and women who graduates in non-STEM and work in non-STEM ($Salary_{00}$). The dependent variable in all columns is annual salary in USD. Census region of job fixed effects are included but not shown. See full set of results in Table B4, Table B5, and Table B6.

Table 10: The Fit of the Model, Decisions and Salaries

	Female	Male
Panel A. Prob(STEM Major)		
Data	0.3703 (0.4831)	0.6340 (0.4818)
Model Prediction	0.3762 (0.4843)	0.6348 (0.4814)
Panel B. Prob(STEM Job)		
Data	0.7311 (0.4439)	0.8117 (0.3911)
Model Prediction	0.6936 (0.4603)	0.7984 (0.4008)
Panel C. $Salary_{11}$		
Data	58280 (11299)	58669 (11072)
Model Prediction	53797 (12089)	56822 (11095)
Panel D. $Salary_{10}$		
Data	48180 (14032)	54358 (13286)
Model Prediction	47307 (14921)	54209 (13865)
Panel E. $Salary_{00}$		
Data	39039 (11370)	45558 (11759)
Model Prediction	40146 (11790)	46902 (11847)

Note: Predicted means and standard deviations (in the parenthesis) are not statistically different from the actual means and standard deviations at any conventional level of significance, except the predicted mean for female $Salary_{11}$ is different from the actual at 10% level. The predicted values come from 1,000,000 simulations based on 1000 bootstraps of the estimated parameters of the model and 1000 random draws from the two ability distributions within each bootstrap.

Table 11: The Fit of the Model, Test Scores

	Female	Male
Panel A. ACT English		
Data	25.661 (4.617)	25.507 (4.640)
Model Prediction	25.683 (4.619)	25.508 (4.634)
Panel B. Communication 114 Grade Points		
Data	3.526 (0.570)	3.339 (0.630)
Model Prediction	3.523 (0.574)	3.339 (0.633)
Panel C. ACT Reading		
Data	25.940 (4.944)	26.278 (4.951)
Model Prediction	25.973 (4.941)	26.277 (4.967)
Panel D. ACT Science		
Data	24.668 (3.960)	26.730 (4.398)
Model Prediction	24.668 (4.080)	26.734 (4.353)
Panel E. exp(High School GPA)		
Data	36.971 (13.043)	35.290 (12.868)
Model Prediction	37.107 (13.578)	35.323 (12.849)
Panel F. ACT Math		
Data	25.645 (4.517)	28.237 (4.185)
Model Prediction	25.666 (5.368)	28.234 (4.160)

Note: The predicted values come from 5,000 simulations based on 50 bootstraps of the estimated parameters of the model and 100 random draws from the two ability distributions within each bootstrap.

Table 12: The Predicted STEM Major Choice by General Intelligence (θ_1) Deciles

Decile	1	2	3	4	5	6	7	8	9	10
Panel A. STEM Major										
Female	0.185	0.246	0.283	0.315	0.346	0.378	0.415	0.462	0.528	0.605
	(0.043)	(0.045)	(0.045)	(0.046)	(0.046)	(0.047)	(0.048)	(0.049)	(0.052)	(0.054)
Male	0.356	0.472	0.535	0.584	0.627	0.668	0.709	0.752	0.797	0.848
	(0.044)	(0.040)	(0.038)	(0.037)	(0.036)	(0.035)	(0.034)	(0.033)	(0.033)	(0.029)
Panel B. STEM Job										
Female	0.627	0.646	0.658	0.667	0.675	0.685	0.694	0.707	0.723	0.743
	(0.129)	(0.105)	(0.094)	(0.087)	(0.081)	(0.076)	(0.071)	(0.068)	(0.067)	(0.070)
Male	0.755	0.770	0.778	0.784	0.791	0.796	0.803	0.810	0.819	0.830
	(0.065)	(0.052)	(0.046)	(0.042)	(0.039)	(0.038)	(0.036)	(0.036)	(0.037)	(0.040)

Note: This predicted values come from 1000,000 replications: 1000 bootstraps each with 1000 replications. Column 1 to 10 present the predicted probability of majoring in STEM (working in STEM) by General Intelligence decile 1–10. Panel A and B show the predicted values of probability of majoring in STEM and probability of working in STEM, respectively.

Table 13: The Predicted STEM Major Choice by Extra Math Ability (θ_2) Deciles

Decile	1	2	3	4	5	6	7	8	9	10
Panel A. STEM Major										
Female	0.253	0.303	0.328	0. 348	0.367	0.384	0.403	0.423	0.450	0.505
	(0.054)	(0.049)	(0.047)	(0.047)	(0.046)	(0.047)	(0.048)	(0.049)	(0.052)	(0.061)
Male	0. 462	0.540	0.579	0.608	0.632	0.655	0.677	0.699	0.726	0.770
	(0.044)	(0.039)	(0.037)	(0.036)	(0.0356)	(0.035)	(0.035)	(0.035)	(0.035)	(0.034)
Panel B. STEM Job										
Female	0.629	0.654	0.667	0.677	0.685	0.693	0.701	0.710	0.720	0.741
	(0.123)	(0.098)	(0.087)	(0.081)	(0.077)	(0.074)	(0.072)	(0.071)	(0.073)	(0.083)
Male	0.758	0.775	0.783	0.789	0.795	0.800	0.805	0.810	0.816	0.828
	(0.060)	(0.048)	(0.043)	(0.041)	(0.039)	(0.038)	(0.037)	(0.037)	(0.038)	(0.041)

Note: This simulation results come from 1000,000 replications: 1000 bootstraps each with 1000 replications. Column 1 to 10 present the predicted probability of majoring in STEM (working in STEM) by Extra Math Ability decile 1–10. Panel A and B show the predicted values of probability of majoring in STEM and probability of working in STEM, respectively.

Table 14: Averaged (across ability distribution) Average Treatment Effects

	(1) Female	(2) Male
Panel A. Averaged ATE of Majoring in STEM (10 vs. 00)		
ATE	7171	7312
	(2240)	(1727)
N	1145	1910
Panel B. Averaged ATE of Working in STEM (11 vs. 10)		
ATE	6480	2612
	(2903)	(1850)
N	424	1211
Panel C. Averaged ATE of Majoring&Working in STEM (11 vs. 00)		
ATE	13651	9925
	(2601)	(1401)
N	1145	1910

Note: This predicted values come from 1000,000 replications: 1000 bootstraps each with 1000 replications. Panel A shows the averaged ATE of majoring in STEM; Panel B shows the averaged ATE of working in STEM; Panel C shows the averaged ATE of majoring and working in STEM. Column (1) and (2) separately show predicted values for female and male. Standard deviations are in parentheses.

Table 15: Counterfactuals of Majoring in STEM

	(1) Female	(2) Male
Proportion of STEM Graduates by Gender		
Factual:	0.3704	0.6354
	(0.0143)	
Counterfactual: replacing $\alpha^{M,A}$, $\alpha^{M,B}$	0.3749	
	(0.0143)	
Counterfactual: replacing θ^{A}, θ^{B}	0.3958	
	(0.0145)	
Counterfactual: replacing $\alpha^{M,A}$, $\alpha^{M,B}$,θ^{A} ,θ^{B}	0.4037	
	(0.0145)	
Counterfactual: replacing β_M	0.4253***	
	(0.0146)	
Counterfactual: replacing X_M	0.5763***	
	(0.0146)	
Counterfactual: replacing β_M and X_M	0.6450***	
	(0.0141)	
N	1145	1910

Standard errors are in parentheses.

Note: This predicted values come from 1000,000 replications: 1000 bootstraps each with 1000 replications. Column (1) shows female predicted probability of majoring in STEM (factual) and counterfactuals. Column (2) shows male predicted probability of majoring in STEM (factual). Row 2–5 show the probability of majoring in STEM when replacing female parameters with the corresponding male parameters. Significant level of the test—$H_0 = H_1$ where $H_0 = female - factual$; $H_1 = female - counterfactual$—are shown as *** p<0.01, ** p<0.05, * p<0.1.

Table 16: Counterfactuals of Working in STEM

	(1) Female	(2) Male
Proportion of STEM Workers in STEM Graduates by Gender		
Factual:	0.7005	0.8020
	(0.0222)	(0.0398)
Counterfactual: replacing $\alpha^{J,A}$, $\alpha^{J,B}$	0.6926	
	(0.0224)	
Counterfactual: replacing θ^{A}, θ^{B}	0.7057	
	(0.0221)	
Counterfactual: replacing $\alpha^{J,A}$, $\alpha^{J,B}$, θ^{A}, θ^{B}	0.6958	
	(0.0223)	
Counterfactual: replacing β_J	0.7512*	
	(0.0210)	
N	424	1211

Standard errors in parentheses.

Note: This predicted values come from 1000,000 replications: 1000 bootstraps each with 1000 replications. Column (1) shows female predicted probability of working in STEM (factual) and counterfactuals. Column (2) shows male predicted probability of majoring in STEM (factual). Row 2–5 show the probability of working in STEM when replacing female parameters with the corresponding male parameters. Significant level of the test—$H_0 = H_1$ where $H_0 = female - factual$; $H_1 = female - counterfactual$—are shown as *** p<0.01, ** p<0.05, * p<0.1.

Table 17: Decomposition of Job Decision

	(1) Exclude	(2) Replace with Male's
Fraction of Graduates in STEM Job		
Factual:	0.7005	
	(0.0222)	
Counterfactual: $\beta_{\text{\#Purdue Graduates in the Same Major}}$	0.4894	0.6440
	(0.0243)	(0.0233)
Counterfactual: $\beta_{\text{\#Purdue Female Graduates in the Same Major}}$	0.8152***	0.6951
	(0.0188)	(0.0224)
Counterfactual: $\beta_{\text{Home State STEM Demand}}$	0.7330	0.7047
	(0.0215)	(0.0222)
Counterfactuals: Year Fixed Effects	0.7492	0.7473
	(0.0210)	(0.0211)
Counterfactuals: Home Region Fixed Effects	0.7671**	0.8209***
	(0.0205)	(0.0186)
N	424	424

Note: The sample includes undergraduate cohorts graduated from 2005–2014. Column (1) shows the counterfactual fraction of female STEM graduates working in STEM for excluding the corresponding predictor. Column (2) shows the counterfactuals of replacing female's coefficient of interest with male's. Standard errors in parentheses. Significant level of the test—$H_0 = factual$; $H_1 = counterfactual$—are shown as *** p<0.01, ** p<0.05, * p<0.1.

Table 18: Fraction of STEM Graduates being Home or Away

	(1) non-STEM	(2) STEM
Panel A. Males		
Away	133	587
	(18.44%)	(81.56%)
Home	95	396
	(19.35%)	(80.65%)
N	228	983
Panel B. Females		
Away	71	220
	(24.4%)	(75.6%)
Home	43	90
	(32.3%)	(67.7%)
N	114	310

Note: Panel A and B separately show summary statistics for males and females. Column (1) shows the number (fraction in parenthesis) of STEM graduates who work in a non-STEM job. Column (2) shows the number (fraction in parenthesis) of STEM graduates who work in a STEM job. "Home" means working in a state where one's home located (reported at college entrance); "Away" means working in another state.

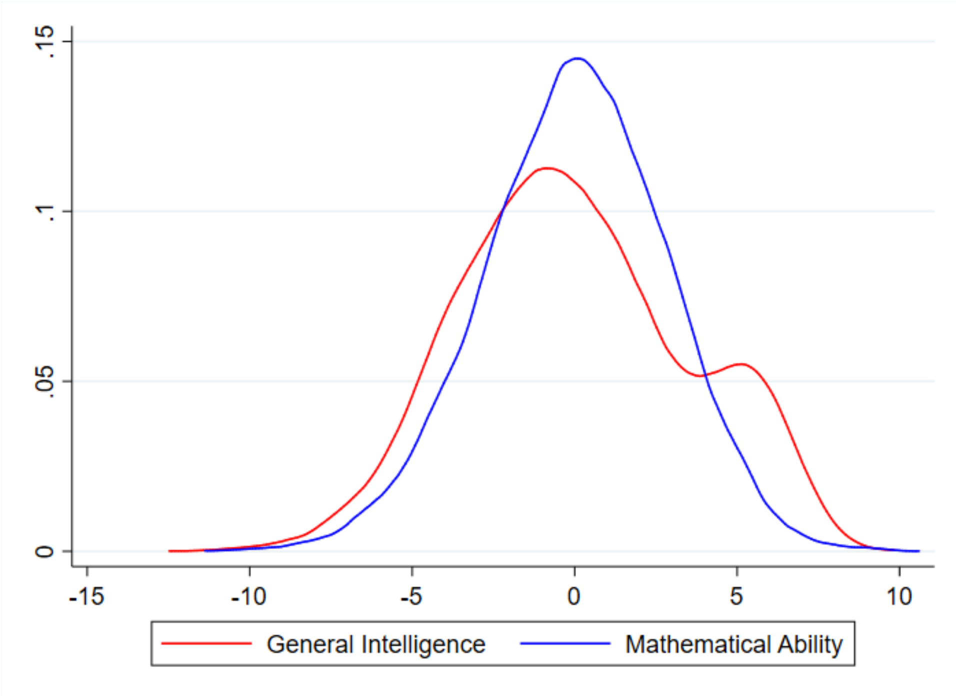

Figure 1: Distributions of Female's Two Abilities
Distributions are centered at mean zero. $sd(f1) = 3.576$; $sd(f2) = 2.801$

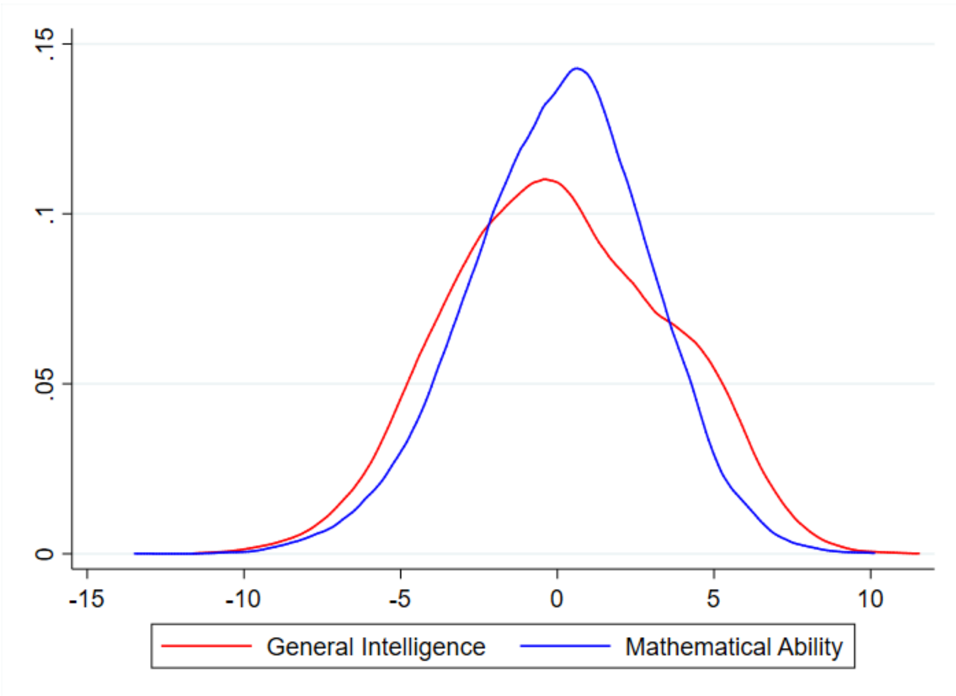

Figure 2: Distributions of Male's Two Abilities
Distributions are centered at mean zero. $sd(f1) = 3.539$; $sd(f2) = 2.862$

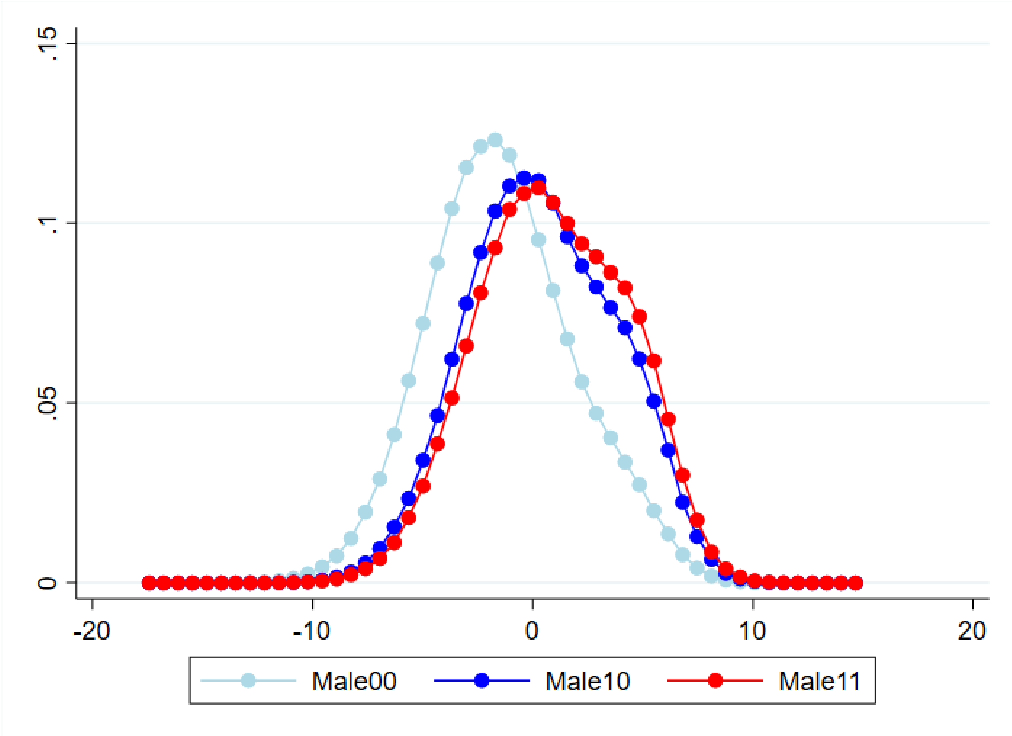

Figure 3: Distribution of Male Factor 1 by Group

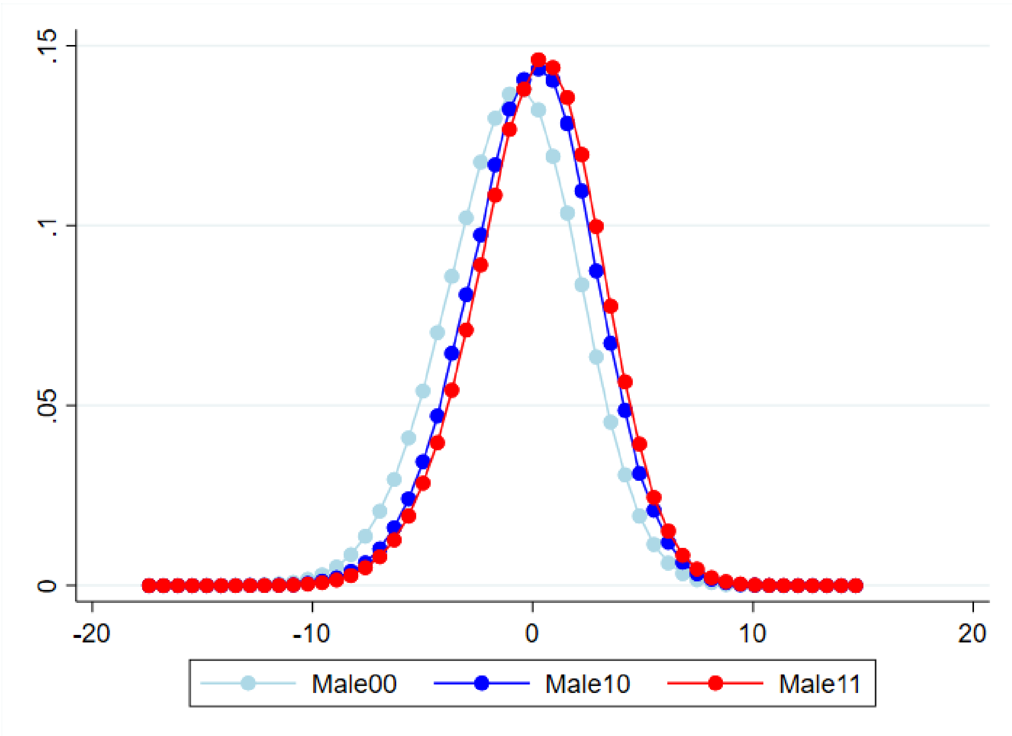

Figure 4: Distribution of Male Factor 2 by Group

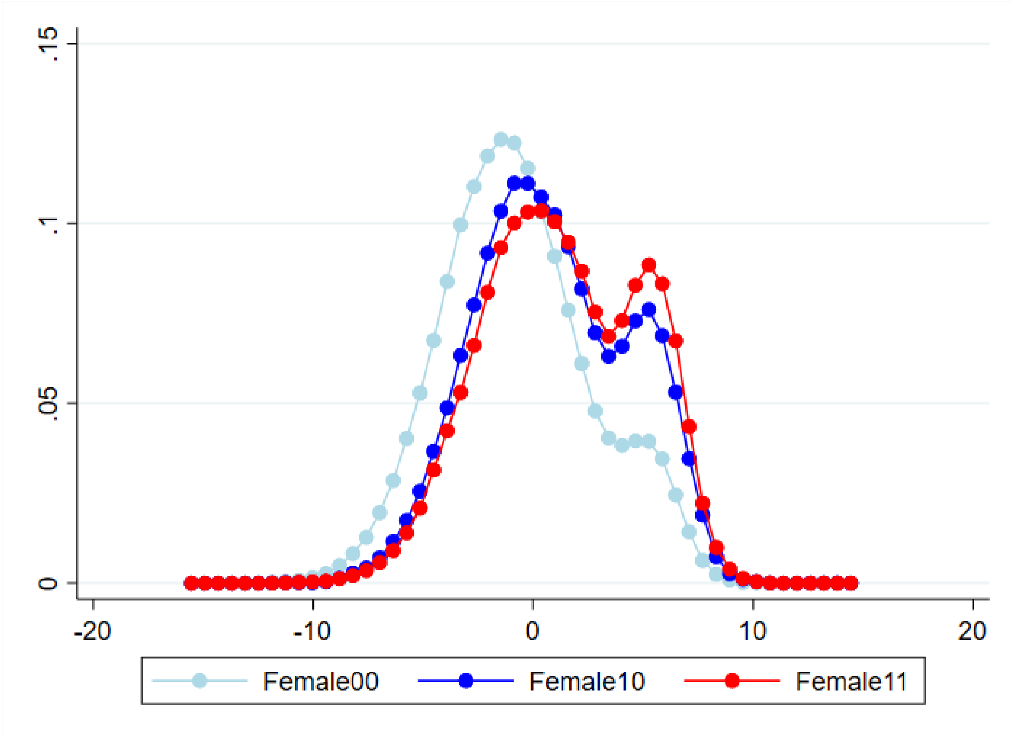

Figure 5: Distribution of Female Factor 1 by Group

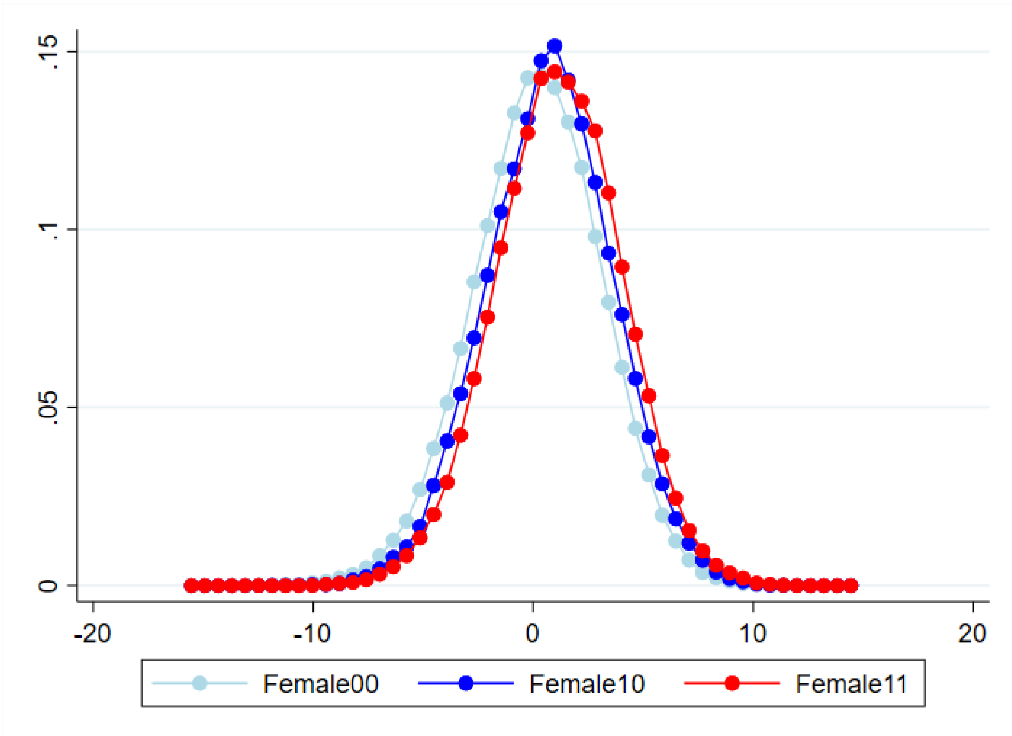

Figure 6: Distribution of Female Factor 2 by Group

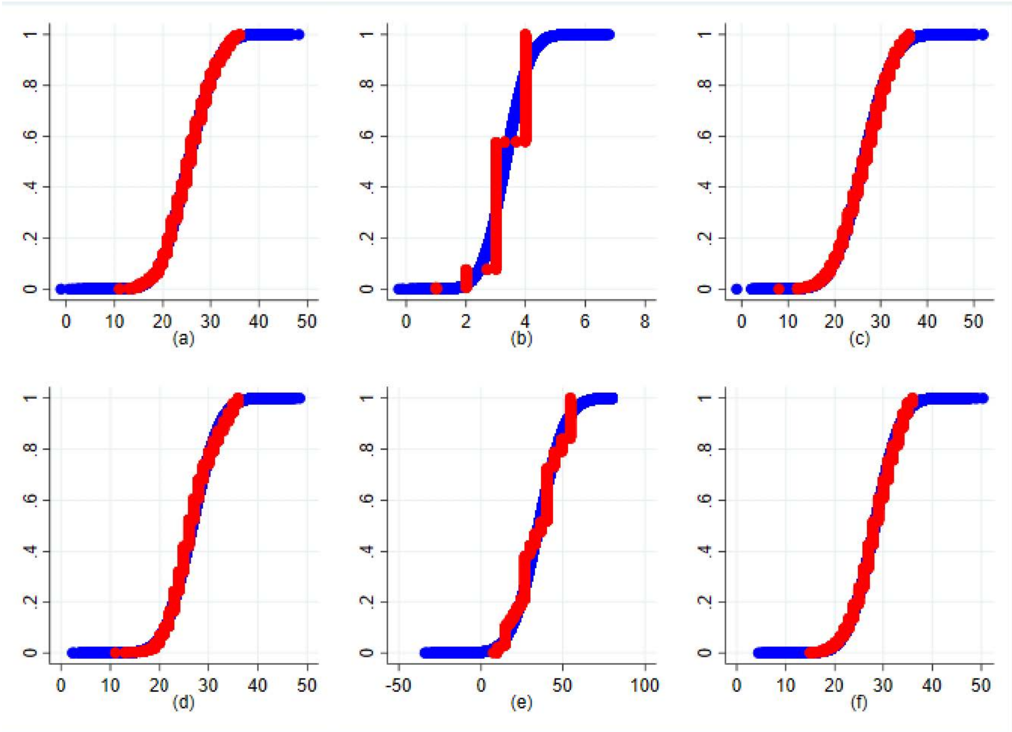

Figure 7: Fit of the Model, Male Test Scores

Notes: Actual (red, dash) and predicted (blue, line) cumulative distributions plotted of the following test scores: (a) ACT English (b) Communication 114 grade points (c) ACT Reading (d) ACT Science (e) exponential high school GPA, and (f) ACT Math. The predicted values come from simulations (10,000 reps) based on the estimated parameters of the model.

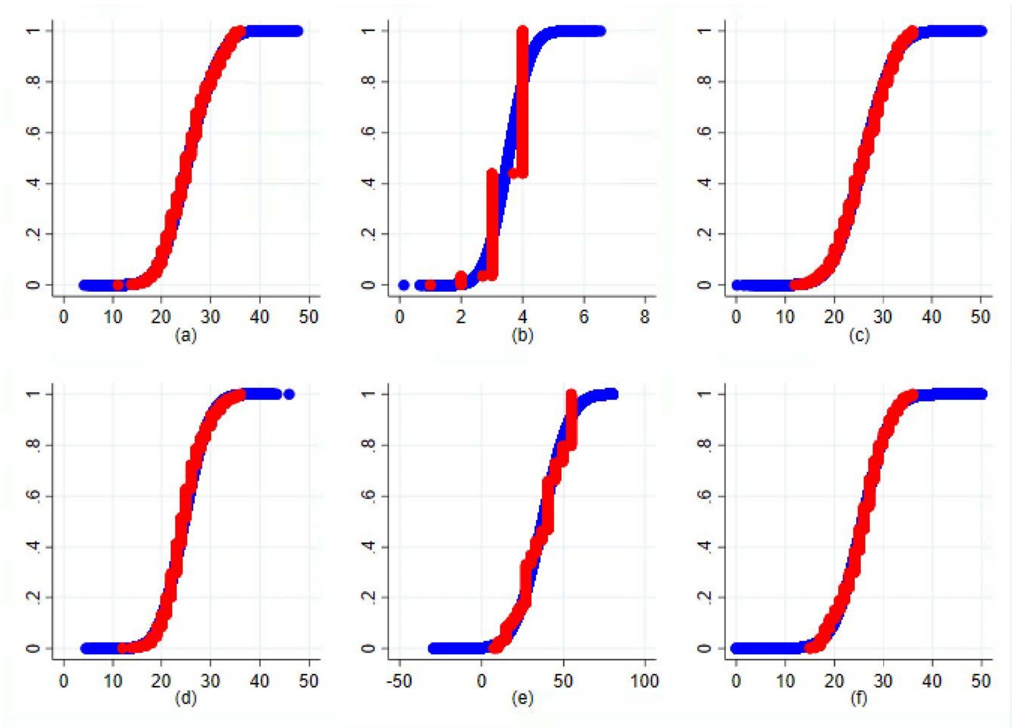

Figure 8: Fit of the Model, Female Test Scores

Notes: Actual (red, dash) and predicted (blue, line) cumulative distributions plotted of the following test scores: (a) ACT English (b) Communication 114 grade points (c) ACT Reading (d) ACT Science (e) exponential high school GPA, and (f) ACT Math. The predicted values come from simulations (10,000 reps) based on the estimated parameters of the model.

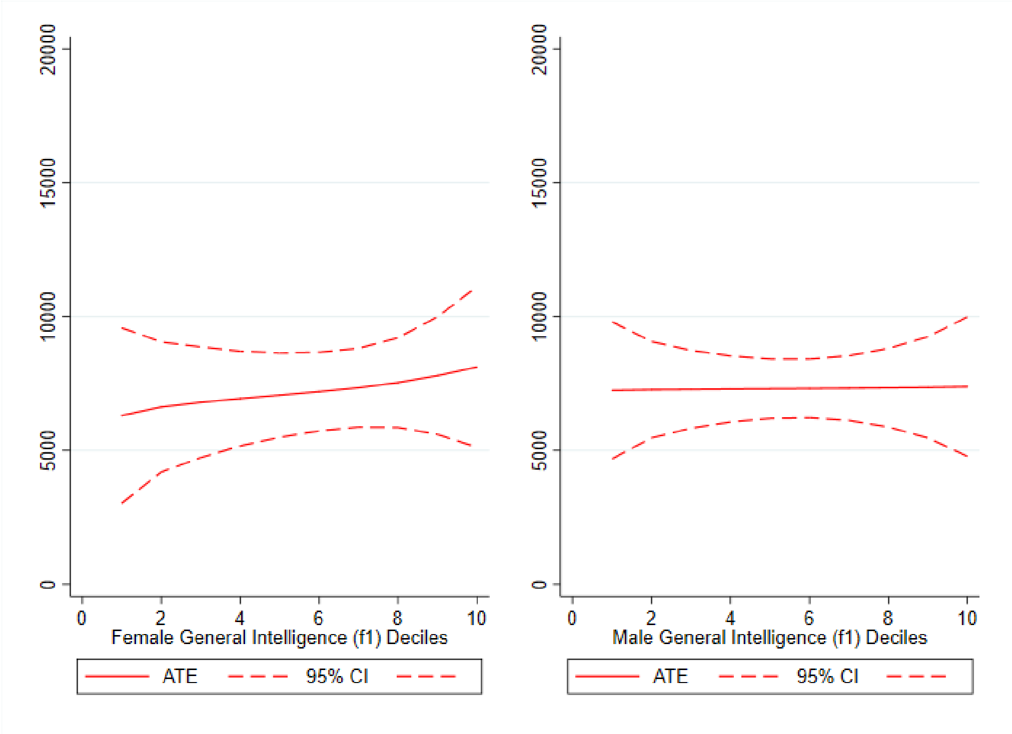

Figure 9: ATE of Majoring in STEM, on General Intelligence

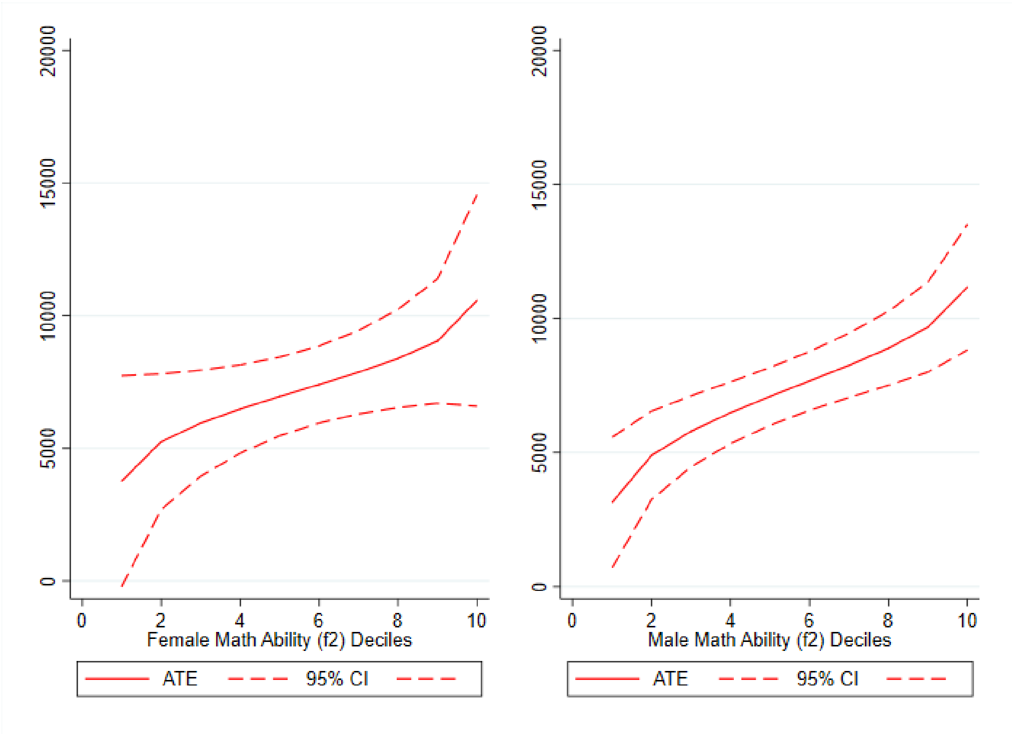

Figure 10: ATE of Majoring in STEM, on Mathematical Ability

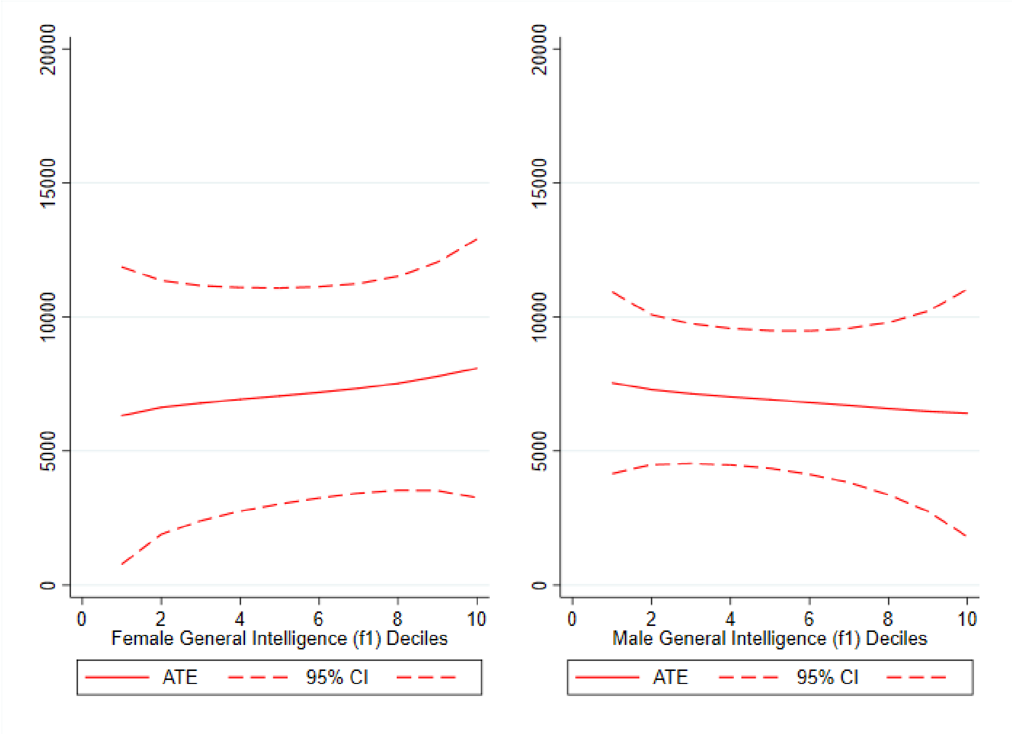

Figure 11: MTE of Majoring in STEM, on General Intelligence

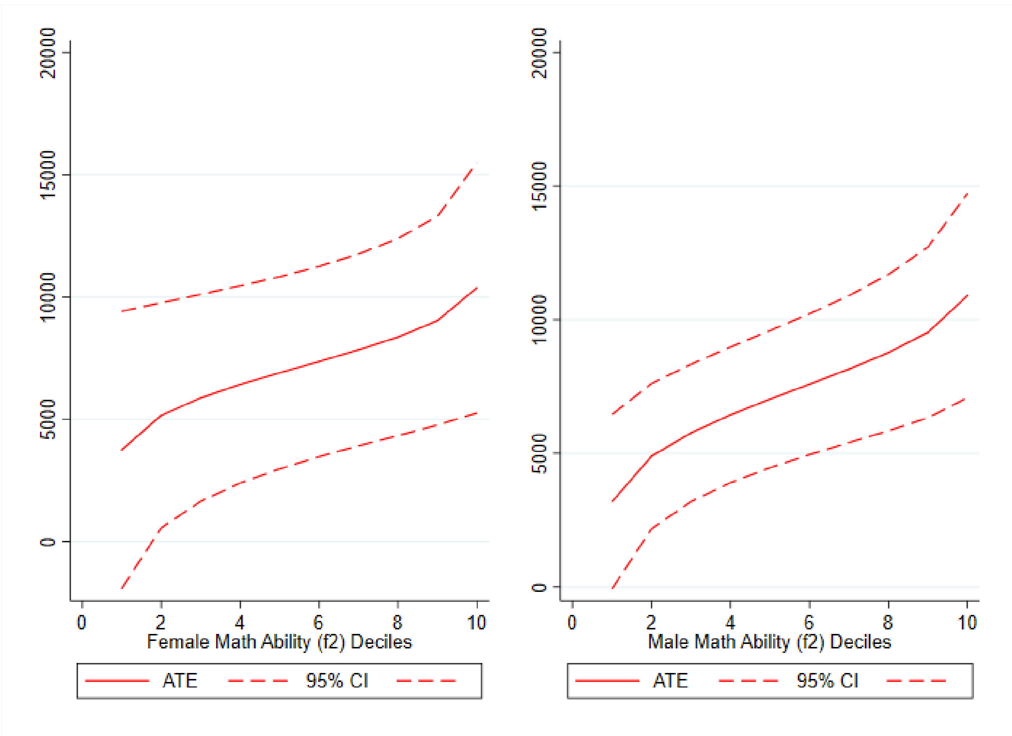

Figure 12: MTE of Majoring in STEM, on Mathematical Ability

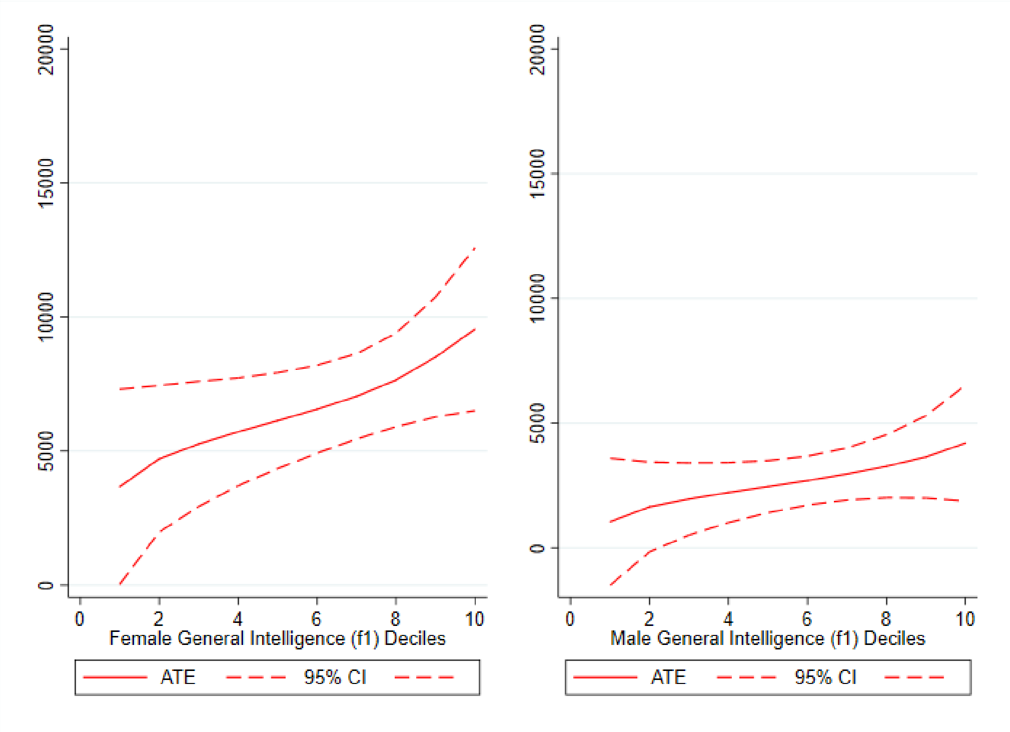

Figure 13: ATE of Working in STEM, on General Intelligence

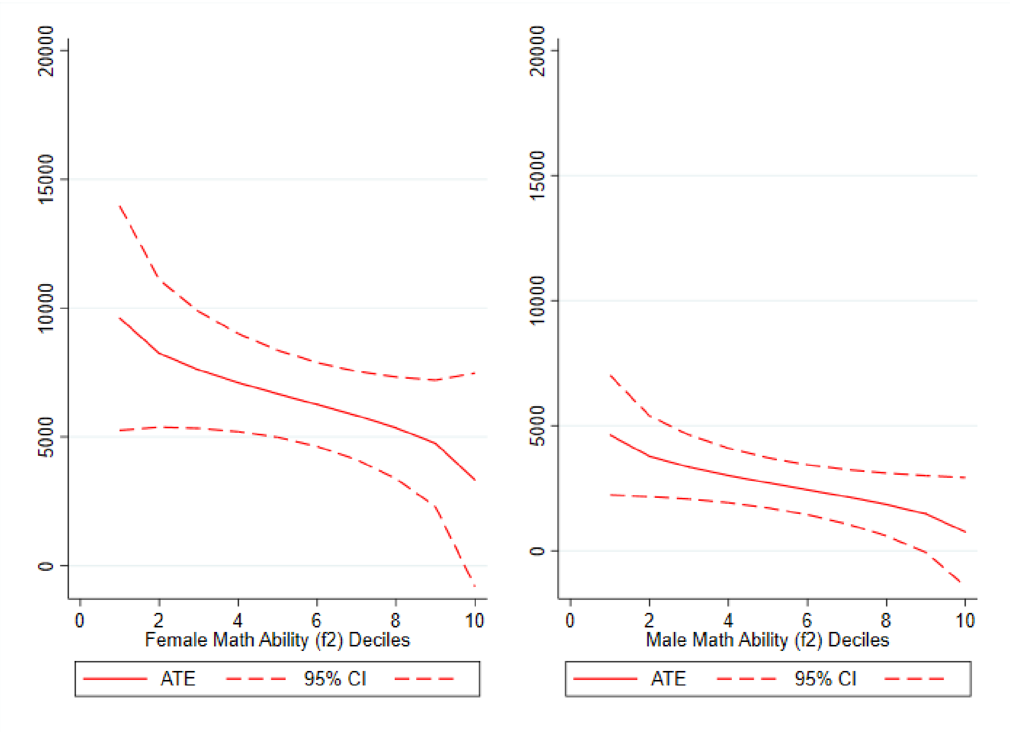

Figure 14: ATE of Working in STEM, on Mathematical Ability

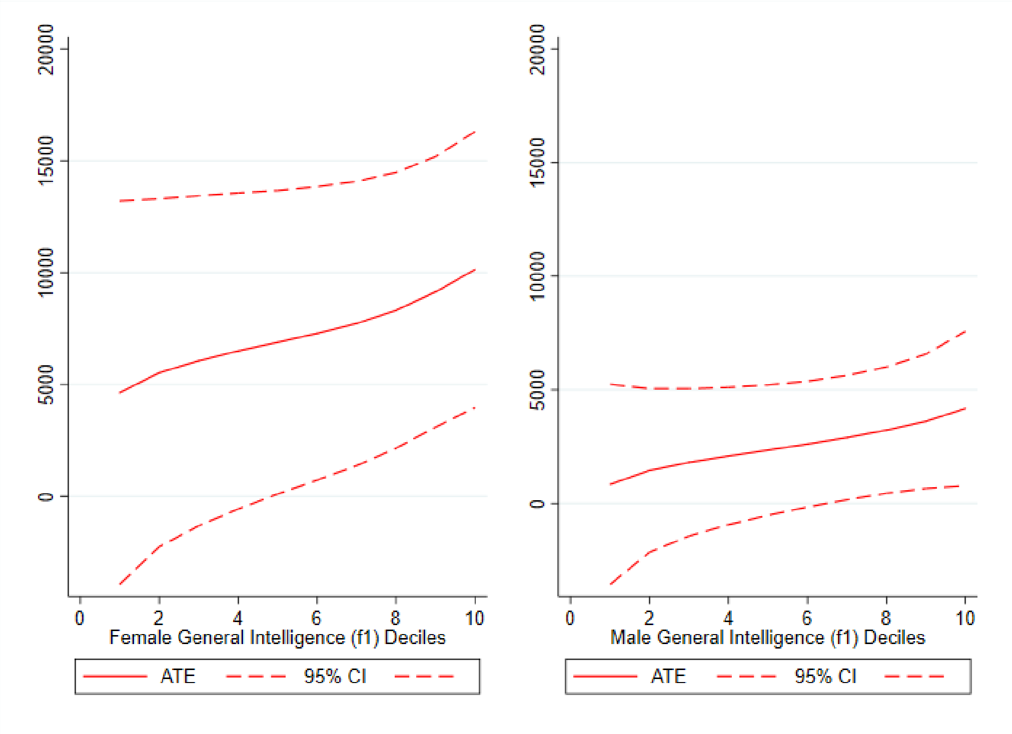

Figure 15: MTE of Working in STEM, on General Intelligence

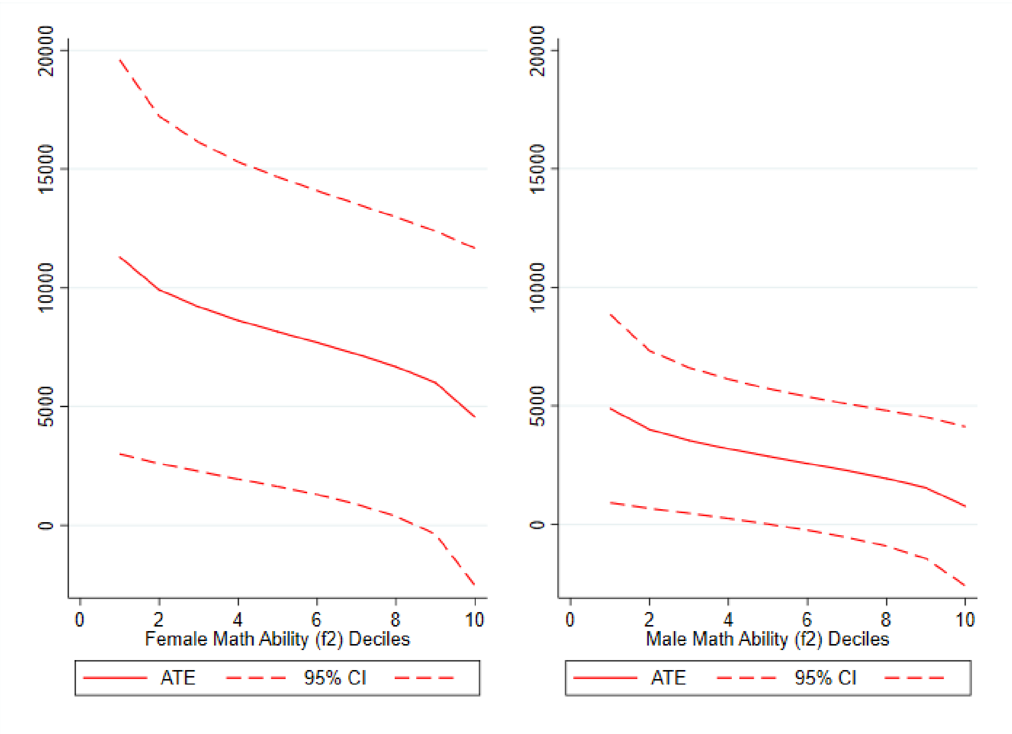

Figure 16: MTE of Working in STEM, on Mathematical Ability

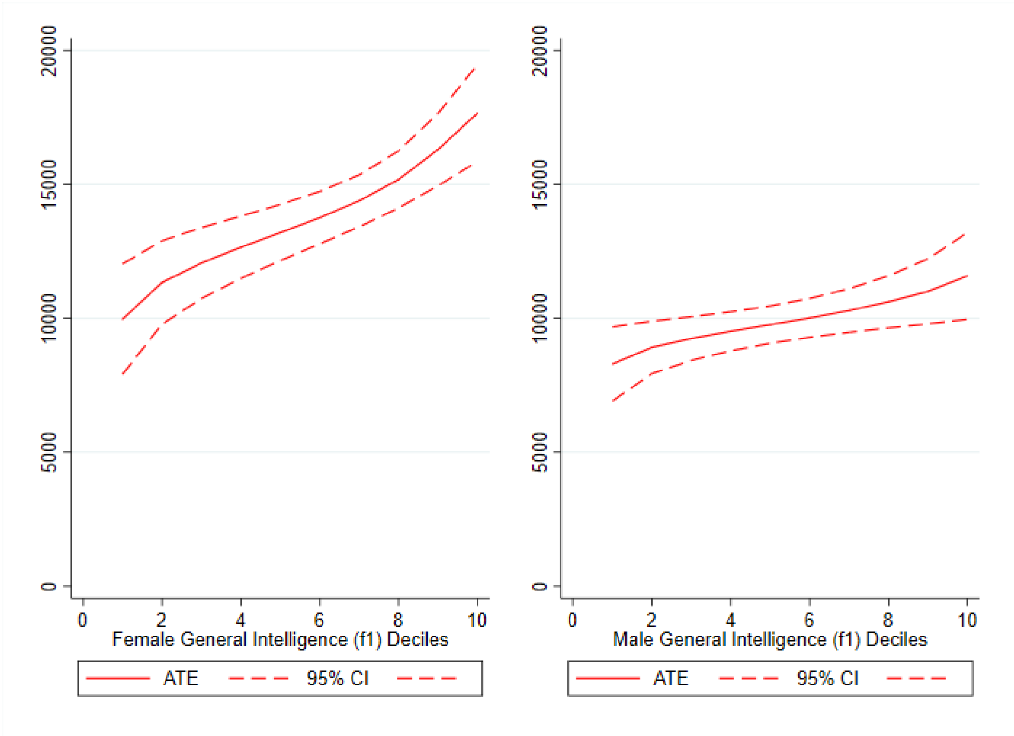

Figure 17: ATE of Majoring and Working in STEM, on General Intelligence

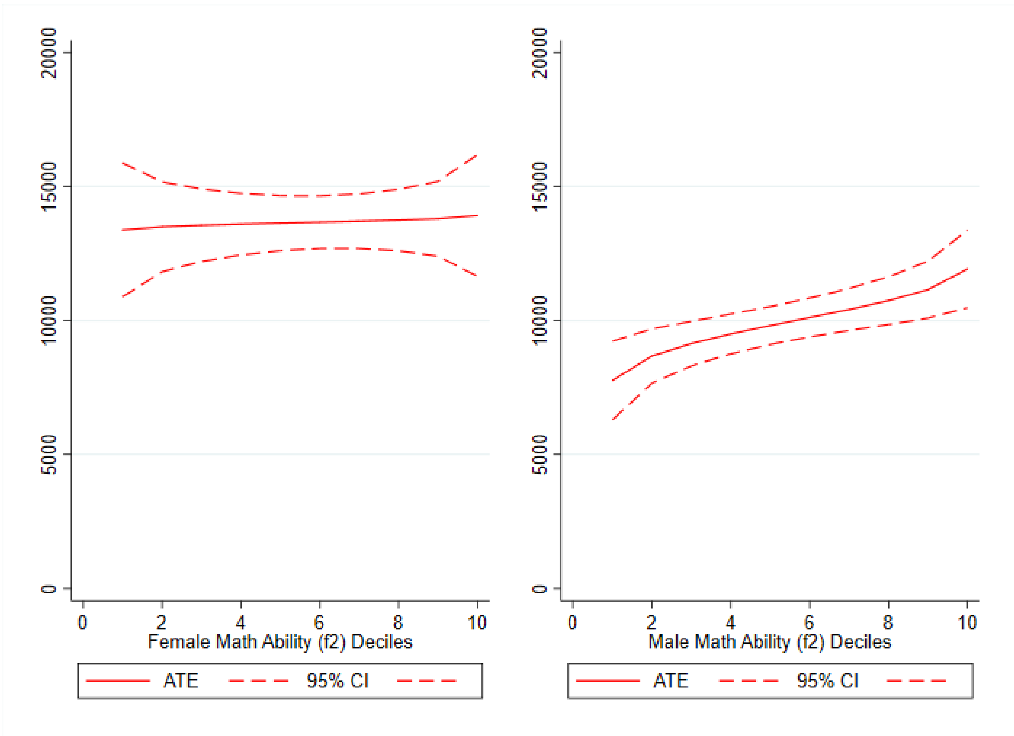

Figure 18: ATE of Majoring and Working in STEM, on Mathematical Ability

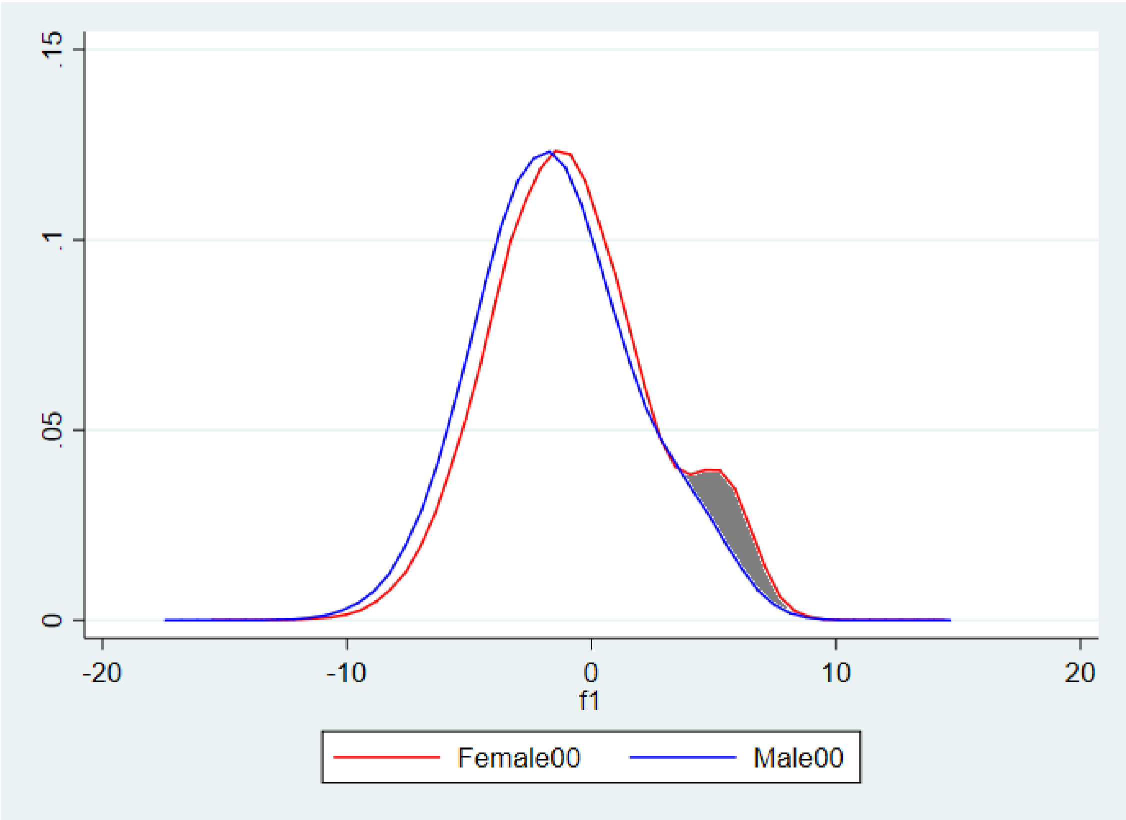

Figure 19: Poor-Sorted High-Ability Women
Note: Overlap the simulated Female00 and Male00 distributions‘

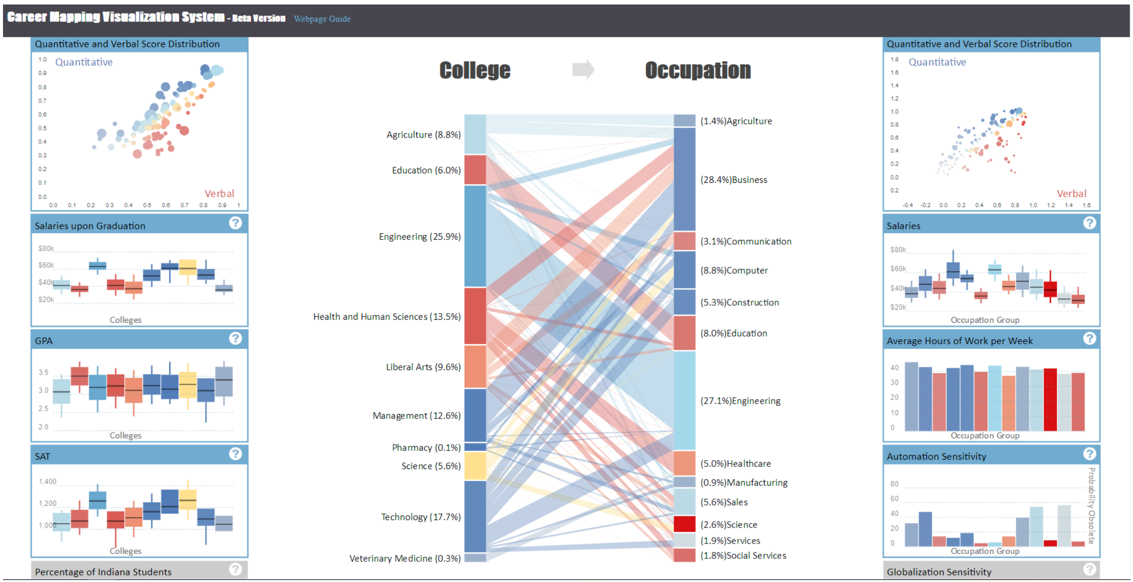

Figure 20: Career Mapping Visualization System
Note: This is a career mapping visualization system developed by Purdue University to show the quantitative and verbal score distributions of each Purdue major and that of each occupation of Purdue graduates.

Appendix A Alternative Setting for The Factors

An alternative restriction to the factor loadings is non-triangular, as follows.

$$\mathbf{\Lambda^T} = \begin{bmatrix} \alpha^{T_1,A} & \alpha^{T_1,B} \\ \alpha^{T_2,A} & \alpha^{T_2,B} \\ \alpha^{T_3,A} & \alpha^{T_3,B} \\ \alpha^{T_4,A} & \alpha^{T_4,B} \\ \alpha^{T_5,A} & \alpha^{T_5,B} \\ \alpha^{T_6,A} & \alpha^{T_6,B} \end{bmatrix} = \begin{bmatrix} \alpha^{T_1,A} & 0 \\ \alpha^{T_2,A} & 0 \\ 1 & 0 \\ 0 & \alpha^{T_4,B} \\ 0 & \alpha^{T_5,B} \\ 0 & 1 \end{bmatrix}$$

where the first factor is identified only from the covariances of $ACT_{English}$, $COM114$, and $ACT_{Reading}$. The second factor is identified from the covariances of $ACT_{Science}$, $HSGPA$ and ACT_{Math}. Therefore, variations in the first factor will only affect the first three scores and variations in the second factor will only affect the rest of three scores. Intuitively, I name the first factor as verbal ability and the second as math ability. Compared to the main specification of the factors in Section 4.1, the alternative sacrifices part of the covariances of the test scores by assuming the first factor does not affect the second set of test scores at all. It might, however, makes it easier to interpret or label the two factors and more importantly, show more variation on the second factor.

Table A1 and A2 shows the estimates of this alternative measurement system. Coefficients of controls are not much different from the main specification. The loadings of verbal skill on the first set of test scores are significantly positive, indicating that an increase in verbal skill will significantly increase $ACT_{English}$, $COM114$ and $ACT_{Reading}$, as expected. Similarly, an increase in math skill will significantly increase $ACT_{Science}$, $HSGPA$ and ACT_{Math}. Specifically, for example, one standard deviation[22] increase in an average woman's verbal skill will increase her $ACT_{English}$ by 3.92 points. One standard deviation increase in an average woman's math skill will increase her ACT_{Math} by 3.77 points. Compared to the main specification of the factors, the loadings of the new second factor have bigger magnitudes due to more variations it takes from the test scores.

I then estimate the same model to analyze the sorting effects in major choice and job choice. The purpose of this estimation is to show the robustness of the main results. Table A3 show the estimates in major choice given the alternative factors. Individuals sort positively on both abilities. Specifically, one standard deviation increase in an average woman's verbal ability will increase her likelihood of graduating in STEM by 5.23% percentage points; and that number for an average man is 6.42%. One standard deviation increase in an average woman's math ability will increase her likelihood of graduating in STEM by 15.83% percentage points; and that number for an average man is 25.98%.

Both genders sort more on math ability than on verbal ability. This is not surprising: the second factor now takes all common variations form $ACT_{Science}$, $HSGPA$ and ACT_{Math}, in contrast to the "leftover" variations of these scores after the first factor has been identified. Additionally, it is intuitive that math ability is more essential to choice between STEM fileds and non-STEM fields than verbal ability. Similar to the estimates in the main specification, we see here men sort more on both abilities as well. Men's coefficients are statistically larger than women's. In job choice, Table A4 shows that no sorting on verbal ability for both gender. Although there is positive sorting on math ability, the gender difference is not significantly different from zero. Overall, the estimates from both specifications of the structures of the factors are qualitatively consistent: men sort more on both

[22] Standard deviation of female's verbal skill is 3.448, female's math skill is 3.770, male's verbal skill is 3.572, male's math skill is 3.937.

latent abilities in major choice; there is no gender difference in sorting on abilities in job choice.

Table A1: Non-triangular Abilities at College Entrance, Female

Dependent Var→	ACT_E	COM114	ACT_R	ACT_S	HSGPA	ACT_M
Home Region: Indiana	-0.754	-0.103	-0.911	-1.710***	0.270	-1.519**
	(0.749)	0.092	(0.804)	(0.585)	(1.995)	(0.653)
Home Region: Midwest	0.981	-0.128*	0.107	-0.322	-4.285**	-0.044
	(0.752)	(0.097)	(0.824)	(0.628)	(2.129)	(0.705)
Home Region: Northeast	-1.273	-0.194*	-0.793	-1.453*	-3.334	-0.814
	(1.218)	(0.146)	(1.298)	(0.883)	(3.071)	(0.949)
Home Region: South	2.323**	-0.049	1.659	0.336	0.472	0.992
	(1.129)	(0.119)	(1.149)	(0.773)	(2.594)	(0.883)
AFGR	0.117***	0.012**	0.097**	0.103***	0.579***	0.109**
	(0.039)	(0.005)	(0.043)	(0.034)	(0.113)	(0.038)
First Term Semester: Fall	1.862*	-0.034	2.574*	1.526	8.516**	2.423
	(1.052)	(0.170)	(1.275)	(1.315)	(4.201)	(1.599)
First Term Semester: Spring	-1.521	0.037	0.752	-0.251	-2.37	-0.100
	(1.607)	(0.254)	(1.915)	(1.966)	(6.270)	(2.398)
General Intelligence	1.138***	0.042***	1			
	(0.049)	(0.005)	X			
Math Ability				0.697***	1.811***	1
				(0.027)	(0.095)	X
Constant	14.669***	2.770***	16.279***	16.168***	-14.099	15.597 ***
	(3.054)	(0.418)	(3.425)	(2.957)	(9.701)	(3.484)
Observations	1,145					

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$

Note: Each column is a separate regression specified in Equation 11. All columns have the same observations: 1145. The loading of Verbal Skill is normalized to one in regression of $ACT_{Reading}$, so that Verbal Skill takes the metrics of $ACT_{Reading}$. The loading of Math Skill is normalized to one in regression of ACT_{Math}, so that Math Skill takes the metrics of ACT_{Math}. I control for annual state-averaged freshmen graduation rate (AFGR) on the year of each student graduated from high school, home census region fixed effects and first enrollment semester fix effects.

Table A2: Non-triangular Abilities at College Entrance, Male

	ACT_E	COM114	ACT_R	ACT_S	HSGPA	ACT_M
Home Region: Indiana	-1.788***	-0.066	-1.707***	-1.726***	0.335	-1.206***
	(0.692)	(0.079)	(0.698)	(0.548)	(1.595)	(0.544)
Home Region: Midwest	-0.590	-0.199**	-0.799	-0.276	-4.919**	-0.160
	(0.714)	(0.083)	(0.726)	(0.571)	(1.673)	(0.563)
Home Region: Northeast	-1.039	-0.195*	-0.941	-0.335	-3.523	-0.406
	(1.019)	(0.118)	(1.035)	(0.758)	(2.300)	(0.712)
Home Region: South	0.476	-0.007	0.296	0.244	0.064	0.776
	(0.757)	(0.091)	(.7799)	(0.626)	(1.844)	(0.613)
AFGR	0.168***	0.018***	0.090**	0.115***	0.664***	0.131***
	(0.029)	(0.004)	(0.033)	(0.029)	(0.086)	(0.027)
First Term Semester: Fall	4.837***	-0.212	3.515**	5.558***	13.106***	5.817***
	(1.076)	(0.180)	(1.276)	(1.152)	(3.545)	(1.063)
First Term Semester: Spring	2.705***	-0.236	1.210	4.589***	10.850**	4.744***
	(1.354)	(0.225)	(1.601)	(1.417)	(4.403)	(1.289)
General Intelligence	1.180***	0.043***	1			
	(0.049)	(0.004)	X			
Math Ability				0.808***	1.684***	1
				(0.027)	(0.079)	X
Constant	8.7869***	2.2636***	16.952***	13.233***	-26.697***	12.888***
	(2.5743)	(0.379)	(2.8526)	(2.437)	(7.402)	(2.296)
Observations	1,910					

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$

Note: Each column is a separate regression specified in Equation 11. All columns have the same observations: 1910. The loading of Verbal Skill is normalized to one in regression of $ACT_{Reading}$, so that Verbal Ability takes the metrics of $ACT_{Reading}$. The loading of Math Skill is normalized to one in regression of ACT_{Math}, so that Math Skill takes the metrics of ACT_{Math}. I control for annual state-averaged freshmen graduation rate (AFGR) on the year of each student graduated from high school, home census region fixed effects and first enrollment semester fix effects.

Table A3: Likelihood of Graduating with A STEM Major (nontriangular)

	(1) Female	(2) Male
	Marginal Effects at the Mean	
Verbal Ability	0.015**	0.018***
	(0.0071)	(0.0064)
Math Ability	0.042***	0.066***
	(0.0059)	(0.0052)
N	1145	1910

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$

Note: This table is different with Table 6 in terms of the loadings structure of two factors. Column (1) and column (2) show the marginal effect of probit at the means for the female and male sample, respectively. All marginal effects reflect to changes in probability of graduating in STEM with one unit increase in the corresponding ability. The standard deviation of female's and male's verbal ability is 3.488 and 3.572; the standard deviation of female's and male's math ability is 3.770 and 3.937. The dependent variable in both column (1) and (2) is dummy of majoring in STEM. Number of Purdue graduates in the same major, number of Purdue female graduates in the same major, first enrollment year, first enrollment semester, degree year fixed effects are controlled but not shown in this table for short.

Table A4: Likelihood of STEM Graduates Work in STEM Occupations (nontriangular)

	(1) Female	(2) Male
	Marginal Effects at the Mean	
Verbal Ability	0.001	0.004
	(0.0119)	(0.0062)
Math Ability	0.023**	0.013***
	(0.0108)	(0.0050)
N	1145	1910

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$

Note: This table is different with Table 7 in terms of the loadings structure of two factors. Column (1) and column (2) show the marginal effect of probit at the means for the female and male sample, respectively. All marginal effects reflect to changes in probability of working in STEM with one unit increase in the corresponding ability of STEM graduates. The standard deviation of female's and male's verbal ability is 3.488 and 3.572; the standard deviation of female's and male's math ability is 3.770 and 3.937. The dependent variable in both column (1) and (2) is dummy of working in STEM. Number of Purdue graduates in the same major, number of Purdue female graduates in the same major, home state STEM demand, degree year fixed effects, home region fixed effects are controlled but not shown in this table for short.

Appendix B

Table B1: Selection: Self-report First Job Information

	(1) Female	(2) Male
General Intelligence	0.0070428	-0.0057017
	(0.0083508)	(0.0077115)
Extra Mathematical Ability	0.0007466	0.0153035**
	(0.0072008)	(0.006406)
N	4565	5640

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$

Note: Column (1) and column (2) show the factor loadings but not the marginal effects. The dependent variable in both column (1) and (2) is dummy of self-reporting first job. Number of Purdue graduates in the same major, number of Purdue female graduates in the same major, first enrolled year fixed effect, first enrolled semester fixed effects, degree year fixed effects, degree semester fixed effects, and home region fix effects are controlled but not shown in this table for short. The estimates show that women who reported to the survey do not differ on both abilities from women who did. Although there is a positive and significant effect on men's extra math ability, the magnitude is too small to have significant economic meaning. Using the loading to calculate the marginal effect, I get one standard deviation increase in extra math ability will increase the probability for an average man to report his first job information by 1.5 percentage points.

Table B2: Likelihood of Graduating with A STEM Major, Full Table

	(1) Female	(2) Male
# Purdue Graduates in Same Major	0.00812***	0.00838***
	(0.000959)	(0.000789)
# Purdue Female Graduates in Same Major	-0.0322***	-0.0366***
	(0.00224)	(0.00218)
First Enrollment Year = 2001	1.881	1.227*
	(1.429)	(0.739)
First Enrollment Year = 2002	1.764*	1.159
	(0.933)	(0.717)
First Enrollment Year = 2003	1.192*	0.903*
	(0.706)	(0.493)
First Enrollment Year = 2004	1.064*	0.869*
	(0.612)	(0.446)
First Enrollment Year = 2005	0.711	0.949**
	(0.542)	(0.397)
First Enrollment Year = 2006	0.289	0.632*
	(0.473)	(0.355)
First Enrollment Year = 2007	0.535	0.632**
	(0.440)	(0.316)
First Enrollment Year = 2008	0.437	0.609**
	(0.362)	(0.284)
First Enrollment Year = 2009	0.185	0.643**
	(0.292)	(0.259)
First Enrollment Semester = Fall	4.899	1.369**
	(91.41)	(0.651)
First Enrollment Semester = Spring	4.293	1.385*
	(91.42)	(0.751)
Degree Year = 2007	0.241	-1.361**
	(0.750)	(0.498)
Degree Year = 2008	0.464	-0.998**
	(0.791)	(0.455)
Degree Year = 2009	0.954	-1.098**
	(0.864)	(0.401)
Degree Year = 2010	0.810	-0.796**
	(0.911)	(0.356)
Degree Year = 2011	1.554*	-0.625**
	(0.936)	(0.316)
Degree Year = 2012	1.355	-0.704**
	(0.963)	(0.275)
Degree Year = 2013	1.511	-0.683**
	(0.977)	(0.243)
Degree Year = 2014	1.956*	0.2958
	(1.021)	(0.9227457)
Degree Semester = Fall	0.203	-0.161
	(0.373)	(0.287)
Degree Semester = Spring	-0.0614	-0.328
	(0.343)	(0.270)
General Intelligence	0.144***	0.182***
	(0.0175)	(0.0155)
Mathematical Ability	0.102***	0.135***
	(0.0253)	(0.0173)
Constant	-6.372	-0.408
	(91.42)	(0.714)
N	1145	1910

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$

Note: The table shows the coefficients and the loadings (not the marginal effects) for the major choice model. The dependent variable in both column (1) and (2) is a dummy of graduating in a STEM major. First enrollment year = 2010, Degree Year = 2005 and Degree Year = 2006 are omitted due to collinearity.

Table B3: Likelihood of STEM Major Graduates Working in A STEM Occupation

	(1) Female	(2) Male
# Purdue Graduates in The Same Major	0.00563***	0.00390***
	(0.00118)	(0.000758)
# Purdue Female Graduates in The Same Major	-0.0148***	-0.0155***
	(0.00404)	(0.00416)
Home State STEM Demand	-0.000000573	-0.000000500
	(0.000000787)	(0.000000431)
Degree Year = 2005	-4.086	0*
	(3.79)	(.)
Degree Year = 2006	-3.795	-1.644**
	(13.69)	(0.673)
Degree Year = 2007	0.424	-0.158
	(0.386)	(0.196)
Degree Year = 2008	0.290	0.0687
	(0.333)	(0.191)
Degree Year = 2009	-0.215	-0.0344
	(0.303)	(0.193)
Degree Year = 2010	-0.0269	0.00299
	(0.340)	(0.181)
Degree Year = 2011	-0.314	-0.112
	(0.265)	(0.171)
Degree Year = 2012	-0.401*	0.0933
	(0.242)	(0.153)
Degree Year = 2013	-0.230	0.0106
	(0.236)	(0.142)
Home Region = Indiana	-0.652	-0.214
	(0.641)	(0.263)
Home Region = Midwest	-0.495	-0.0814
	(0.574)	(0.244)
Home Region = Northeast	-1.116	-0.364
	(0.706)	(0.329)
Home Region = South	-0.700	0.178
	(0.590)	(0.279)
General Intelligence	0.0492*	0.0366**
	(0.0282)	(0.0186)
Mathematical Ability	0.0490	0.0365*
	(0.0410)	(0.0221)
Constant	1.171	0.919**
	(0.718)	(0.302)
N	424	1211

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: The table shows the coefficients and the loadings (not the marginal effects) for the job choice model. The dependent variable in both column (1) and (2) is a dummy of working in a STEM occupation. Degree Year = 2014, and Home Region = West are omitted due to collinearity.

Table B4: Salary of 11 Type (STEM Major, STEM Job)

	(1) Female	(2) Male
State Annual Unemployment Rate	-136.0	-838.7**
	(608.5)	(358.5)
STEM Fraction of Total Employment	-3004239.8	-181322.5
	(2962201.5)	(1713905.1)
# STEM Total Employment	0.0176	-0.0000960
	(0.0242)	(0.0140)
# non-STEM Total Employment	-0.000920	-0.0000357
	(0.00100)	(0.000582)
# Total Graduates	1.091	1.209*
	(1.382)	(0.668)
# Total STEM Graduates	0.477	-1.201
	(2.689)	(1.296)
# Female Graduates	-1.464	-2.126
	(3.218)	(1.536)
# Female STEM Graduates	-1.766	2.517
	(7.639)	(3.655)
Job Region = New England	7929.5**	6977.5**
	(3272.5)	(2449.5)
Job Region = Mid-Atlantic	13217.5***	7353.3***
	(3136.3)	(1570.9)
Job Region = East North Central	6957.2***	6077.3***
	(1465.9)	(844.5)
Job Region = West North Central	8486.6***	4197.4**
	(2447.5)	(1707.9)
Job Region = South Atlantic	9137.6***	7310.8***
	(2113.0)	(1200.1)
Job Region = East South Central	8825.2**	5050.3**
	(3875.7)	(1697.4)
Job Region = West South Central	13856.0***	12931.2***
	(2195.1)	(1289.0)
Job Region = Mountain	8118.4**	3855.0*
	(2847.4)	(2139.1)
Job Region = Pacific	14331.6***	17012.6***
	(2502.0)	(1261.4)
General Intelligence	775.7***	424.6**
	(217.6)	(129.1)
Mathematical Ability	-938.0**	-714.4***
	(319.6)	(160.4)
Constant	16264.1	58553.7
	(227334.2)	(115951.0)
N	310	983

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Column (1) and column (2) show the coefficients and the loadings for the female and male sample, respectively. The dependent variable in both column (1) and (2) is self-reported annual salary. Job Region = Indiana is omitted due to collinearity.

Table B5: Salary of 10 Type (STEM Major, non-STEM Job)

	(1) Female	(2) Male
State Annual Unemployment Rate	245.0	-1059.2
	(1579.2)	(883.1)
STEM Fraction of Total Employment	-2565034.6	-2578088.3
	(7425402.7)	(4294849.1)
# STEM Total Employment	0.0237	0.0257
	(0.0612)	(0.0358)
# non-STEM Total Employment	-0.000836	-0.000970
	(0.00254)	(0.00148)
# Total Graduates	0.321	2.874
	(1.904)	(1.756)
# Total STEM Graduates	1.025	-3.618
	(2.614)	(2.976)
# Female Graduates	-0.466	-6.163
	(3.790)	(3.866)
# Female STEM Graduates	-2.796	10.01
	(6.468)	(8.101)
Job Region = New England	12727.1	2751.4
	(8286.8)	(12191.4)
Job Region = Mid-Atlantic	14399.8**	1883.4
	(4673.7)	(4474.4)
Job Region = East North Central	15747.4***	5746.9**
	(2576.2)	(2091.6)
Job Region = West North Central	7791.1	3538.6
	(5275.8)	(3523.7)
Job Region = South Atlantic	7551.8	13629.4***
	(6036.8)	(3423.8)
Job Region = East South Central	10576.4**	-980.4
	(5255.9)	(5541.4)
Job Region = West South Central	8632.4	6063.9
	(6521.1)	(3884.3)
Job Region = Mountain	11319.4	15231.7**
	(12051.8)	(4770.5)
Job Region = Pacific	6931.7	14658.0***
	(5406.7)	(4276.6)
General Intelligence	301.1	164.0
	(420.0)	(343.3)
Mathematical Ability	-1518.6**	-1095.8**
	(606.1)	(374.6)
Constant	200091.5	453778.7
	(401613.8)	(312401.1)
N	114	228

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Column (1) and column (2) show the coefficients and the loadings for the female and male sample, respectively. The dependent variable in both column (1) and (2) is self-reported annual salary. Job Region = Indiana is omitted due to collinearity.

Table B6: Salary of 00 Type (non-STEM Major, non-STEM Job)

	(1) Female	(2) Male
State Annual Unemployment Rate	-998.7*	-31.02
	(586.9)	(578.5)
STEM Fraction of Total Employment	-2051633.9	-137548.0
	(2227097.8)	(2321971.8)
# STEM Total Employment	0.0140	0.00263
	(0.0185)	(0.0190)
# non-STEM Total Employment	-0.000669	-0.0000751
	(0.000764)	(0.000790)
# Total Graduates	0.965	-0.150
	(0.737)	(1.022)
# Total STEM Graduates	-0.749	-0.879
	(1.258)	(1.951)
# Female Graduates	-1.561	-0.200
	(1.565)	(2.316)
# Female STEM Graduates	1.300	2.954
	(3.300)	(5.391)
Job Region = New England	6053.4**	6089.6*
	(2989.4)	(3266.6)
Job Region = Mid-Atlantic	6998.5**	7861.3**
	(2425.6)	(2978.0)
Job Region = East North Central	7027.8***	7453.3***
	(986.2)	(1072.5)
Job Region = West North Central	6465.0**	9657.1***
	(2338.5)	(2243.7)
Job Region = South Atlantic	4876.7**	6405.3***
	(1656.4)	(1782.5)
Job Region = East South Central	4275.7*	6027.3**
	(2320.4)	(2843.8)
Job Region = West South Central	4799.1*	9642.3***
	(2510.7)	(2253.3)
Job Region = Mountain	4597.0*	3237.2
	(2462.7)	(2028.4)
Job Region = Pacific	7462.1**	7880.8***
	(2459.5)	(2175.9)
General Intelligence	154.7	153.4
	(158.1)	(175.7)
Mathematical Ability	-888.6***	-302.8
	(216.0)	(193.0)
Constant	75672.5	152025.6
	(134046.8)	(168848.6)
N	721	699

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Column (1) and column (2) show the coefficients and the loadings for the female and male sample, respectively. The dependent variable in both column (1) and (2) is self-reported annual salary. Job Region = Indiana is omitted due to collinearity.